SIMULATION-BASED OPTIMIZATION FOR DECISION MAKING UNDER UNCERTAINTY IN OPENCAST MINES

MASOUD SOLEYMANI SHISHVAN

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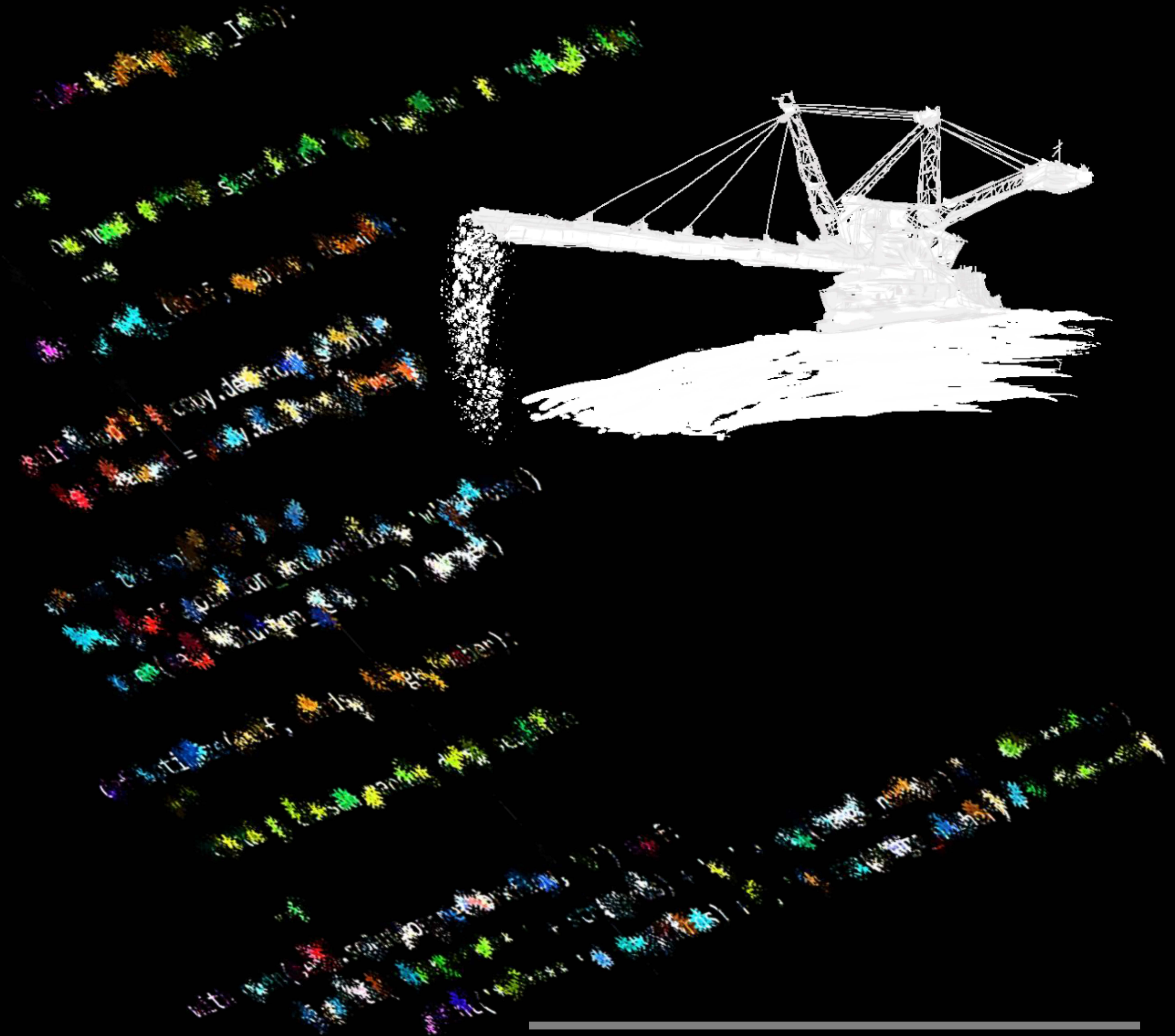

DELFT UNIVERSITY OF TECHNOLOGY

Propositions

accompanying the dissertation

SIMULATION-BASED OPTIMIZATION FOR DECISION MAKING UNDER UNCERTAINTY IN OPENCAST MINES

by

Masoud SOLEYMANI SHISHVAN

1. The complex interaction between the objectives, all mining elements, and the deposit model does not allow for a closed form optimization problem to be formulated. Hence, existing methods tend to oversimplify the dynamics and the stochasticity of the real system. (Dissertation)

2. In continuous coal mining operations, geological uncertainty does not only affect the quality/amount of coal produced, but also affects over and inter-burden management and delays dispatching. (Dissertation)

3. Simulation techniques, including geostatistical simulation and discrete-event simulation (DES), can be effectively used for decision support in any mining operation. (Dissertation)

4. The Simulation-based Optimization approach leads to significant reductions in downtimes of equipment. (Dissertation)

5. The focus of mining scholars should be on the development of efficient algorithms for the optimization of short-term production scheduling rather than long-term production planning.

6. The traditional Discounted Cash Flow (DCF) valuation method must be replaced by the Real Option Valuation (ROV) method for the calculation of Net Present Value (NPV) of mining projects.

7. PhD Students should not be judged based on their short-term performances, but the long-term achievements.

8. Every PhD Student must be an independent thinker and must not be bound to any limiting constraints.

9. Programmers should first develop their communications skills and then a code.

10. If you want to be successful in mining business, you need to be pragmatic not idealistic.

These propositions are regarded as opposable and defendable, and have been approved as such by the promotors Prof. dr. ir. J. D. Jansen, Prof. dr. -Ing. J. Benndorf, and the daily supervisor Dr. M. W. N. Buxton.

Simulation-based Optimization for Decision Making Under Uncertainty in Opencast Mines

SIMULATION-BASED OPTIMIZATION FOR DECISION MAKING UNDER UNCERTAINTY IN OPENCAST MINES

Dissertation

for the purpose of obtaining the degree of doctor
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by

Masoud SOLEYMANI SHISHVAN

Master of Science in Mining Engineering,
Sahand University of Technology, Iran
Born in Tabriz, Iran

This dissertation has been approved by the promotors.

Composition of the doctoral committee:

Rector Magnificus	chairman
Prof.dr.ir. J.D. Jansen	Delft University of Technology, promotor
Prof.dr.-Ing. J. Benndorf	Freiberg University of Mining and Technology, Germany, promotor

Independent members:

Prof.dr. R.R. Negenborn	Delft University of Technology
Prof. dr.-Ing. C. Niemann-Delius	Emeritus Professor RWTH Aachen, Germany
Dr.-Ing. J. Sattarvand	University of Nevada, Reno, USA
Prof.dr.ir. W.R. Rossen	Delft University of Technology

Other member:

Dr. M.W.N. Buxton	Delft University of Technology

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SUMMARY

A sustainable exploitation of mineral deposits is a complex multi-objective problem. Production management aims to maximize utilization and effective production rates of major mining equipment, minimize specific costs, and ensure compliance to the mine's long-term plan. At the same time, the extracted raw material has to meet tight specifications of customers. For instance, in bulk mining operations, customers' requirements are usually in terms of upper and lower bounds of multiple quality parameters, which have to be met on a train-by-train basis. Furthermore, the overburden covering the deposit has to be excavated, transported, and dumped in a sequence that guarantees safety and long-term stability of the waste dump. In this dissertation, the focus is on opencast coal mining operations.

Coal (hard coal and lignite) will continue to provide a significant contribution to electrical energy supply in Europe during the next decades, supporting the anticipated change towards increasing use of renewable energy sources. During these three to four decades, many steps have to be taken to maintain a secure and affordable power supply while reducing CO_2 *emissions and introducing new, but currently unknown technologies. Thus, the coal sector puts a strong focus on research and development into the future technologies that will be needed to keep coal in a sustainable and competitive energy mix.*

If geological conditions are reasonably constant, coal (lignite) can be extracted from deposits utilizing continuous mining systems. Continuous mining systems require large investments and operational costs. Decisions in daily production scheduling are impacted by uncertainties, such as the incomplete knowledge about the deposit and operational downtimes. These can have a significant influence on the actual production performance. Furthermore, the complex interaction between the aforementioned objectives, all mining elements, and the deposit model does not allow formulating a closed form optimization problem to find optimal or good decisions. Optimization methods, especially those that are applied in real-world problems, formulate the decision problems into mathematical models. They tend to oversimplify the dynamics and the stochasticity of the real system. This reason motivates us to explore an alternative approach.

This dissertation proposes a stochastic based mine process simulator capable of capturing different sources of uncertainty, including geological uncertainty and unscheduled breakdowns of equipment. Throughout this study, two types of simulations, namely Monte-Carlo simulation and Discrete-Event Simulation (DES), are integrated. Results show that such an approach provides the mine-planning engineer a valuable tool to foresee critical situations affecting the continuous supply of raw material to the customers and the system performance.

This dissertation further proposes a new simulation-based optimization algorithm applicable to short-term production planning of opencast mines. The deterministic optimization and the stochastic simulation are combined in a closed loop. The proposed approach is capable of optimizing dispatch decisions for the given extraction sequences. The following gives an overview of different chapters of the dissertation.

Chapter 1 *gives a brief background on opencast coal mining. The chapter further presents the research objectives to guide the development of the method. The chapter finally concludes with a dissertation outline.*

Chapter 2 *provides a detailed problem specification of the case studies. In this dissertation, the performance of the developed concepts will be demonstrated in two different real-size case studies. Complete descriptions of the case studies together with the challenges and problems are presented.*

Chapter 3 *reviews the state-of-the-art on stochastic simulation and simulation-based optimization. Furthermore, it provides the theoretical background of the developed algorithmic approach for simulation-based optimization of continuous mining system processes.*

Chapter 4 *presents a synthetic experiment in a fully controllable environment. It demonstrates that the developed concept is capable of quantifying the effects of geological uncertainty, unscheduled downtimes, and their impacts on the ability of delivering contractually defined coal quantities and qualities.*

Chapter 5 *extends the developed simulation model in the previous chapter to a new level by implementing it in an industrially relevant environment. Results of both case studies are used to describe the details of the simulation modeling framework, and to illustrate the strength and limitations of its application.*

Chapter 6 *proposes a new multi-stage simulation-based optimization approach to optimize the dispatch system in terms of minimum idle time due to unavailability of dumping space. This approach consists of running alternatingly a deterministic optimization model and a stochastic simulation model. It combines simulation, a transportation problem, and a job-shop scheduling problem. A control module is used to suggest refinements to parameters of the optimization model after each loop iteration. The iterative process ends after a stopping criterion is met.*

Chapter 7 *gives an overview of the main conclusions from this study. The chapter further provides a list of recommendations and future research possibilities.*

SAMENVATTING

Duurzame winning van minerale voorkomens is een complex probleem met verschillende doelstellingen. Productiemanagement heeft als doel om inzet van kapitaalgoederen te maximaliseren met effectieve inzet van produktiemiddelen tegen minimale kosten terwijl de doelstellingen op lange termijn worden behaald. Tegelijkertijd moet het gewonnen erts voldoen aan strenge kwaliteitseisen van de klant. In bulkmijnbouwoperaties eist de klant meestal kwaliteiten van diverse bestanddelen binnen grenzen, die per treinlading worden voorgeschreven. Bovendien moet de deklaag worden afgegraven, getransporteerd en gestort in een volgorde die veiligheid en stabiliteit van het stort garandeert op lange termijn.

Kolen zullen de komende decennia een aanzienlijk aandeel blijven leveren aan de energievoorziening in Europa ter ondersteuning van de verwachte transitie naar duurzame energiebronnen. Gedurende deze drie tot vier decennia moeten er veel stappen worden gezet om te voorzien in zekere en betaalbare leveranties van energie bij gereduceerde CO_2-emissies terwijl er alternatieve, nog onbekende technologieën worden geïntroduceerd. Vandaar dat de kolensector een sterke nadruk legt op onderzoek en ontwikkeling van nieuwe technologieën, die nodig zijn om kolen te kunnen blijven handhaven in de energie-mix.

Als geologische omstandigheden redelijk constant zijn, kan bruinkool worden gewonnen met gebruik van continue mijnbouwsystemen. Deze systemen vereisen hoge kapitaalkosten en operationele kosten. Beslissingen in de dagelijkse planning worden beïnvloed door onzekerheden als onvolledige kennis van de ondergrond en operationele factoren. Deze kunnen een significante invloed hebben op de actuele prestaties. Bovendien laat de complexe interactie tussen bovengenoemde doelstellingen, alle mijnbouwgerelateerde factoren en het model van het ertslichaam het niet toe om een afgesloten vorm te formuleren voor het optimalisatieprobleem om optimale en goede besluiten te vinden. Optimalisatie methodes, in het bijzonder diegene die toepasbaar zijn op echte, bestaande problemen, formuleren beslissingsproblemen in wiskundige modellen. Deze hebben de neiging om de dynamiek en stochastiek van het echte systeem te oversimplificeren. Deze reden motiveert ons om een alternatieve benadering te onderzoeken.

Dit proefschrift stelt een proces-simulator van een stochastisch mijnproces voor met de capaciteit om verschillende bronnen van onzekerheid in te kapselen, zoals geologische onzekerheid en ongeplande materieelstoringen. Gedurende deze studie zijn twee soorten simulaties geïntegreerd, te weten Monte-Carlo en Discrete-Event simulaties. Uit de resultaten blijkt dat deze aanpak een waardevol instrument is voor de mijn-planningsingenieur om situaties te voorspellen die kritiek zijn voor de continuïteit van de levering van grondstoffen aan de klant

en voor de prestaties van het systeem. Voorts stelt dit proefschrift een nieuw algoritme voor gebaseerd op simulaties, dat toegepast kan worden bij de productieplanning op korte termijn. De deterministische optimalisatie en stochastische simulatie worden gecombineerd in een gesloten kring. De voorgestelde aanpak is in staat om logistieke beslissingen voor gegeven omstandigheden te optimaliseren.

Hieronder volgt een overzicht van de verschillende hoofdstukken van dit proefschrift.

***Hoofdstuk 1** geeft een kort overzicht van dagbouwwinning van bruinkool. Vervolgens worden de onderzoeksdoelstellingen gepresenteerd om de ontwikkeling van de methode te duiden. Het hoofdstuk sluit af met een opzet van het proefschrift.*

***Hoofdstuk 2** verschaft een gedetailleerde specificatie van het probleem in de onderzochte voorbeeldgevallen. In dit proefschrift worden de prestaties van de ontwikkelde concepten gedemonstreerd in twee verschillende praktijkgevallen. Complexe beschrijvingen van deze praktijkgevallen worden hier gepresenteerd samen met uitdagingen en problemen.*

***Hoofdstuk 3** behandelt de huidige stand van zaken op het gebied van stochastische simulatie en optimalisatie gebaseerd op simulatie. Bovendien wordt de theoretische achtergrond verschaft van de ontwikkelde, stochastische aanpak van de optimalisatie van het continue mijnprocess gebaseerd op simulaties.*

***Hoofdstuk 4** geeft een synthetisch experiment in een volledige gecontroleerde omgeving. Het laat zien dat het ontwikkelde concept in staat is om de effecten van geologische onzekerheid, ongeplande onderbrekingen te kwantificeren alsmede hun impact op het vermogen om contractueel vastgelegde hoeveelheden en kwaliteiten steenkool te leveren.*

***Hoofdstuk 5** bouwt verder op het ontwikkelde simulatiemodel in het vorige hoofdstuk tot een nieuw niveau door het te implementeren in een industriële omgeving. Resultaten van beide praktijkgevallen worden gebruikt om de details van het raamwerk van het simulatiemodel en de sterktes en zwaktes van de toepassing te beschrijven.*

***Hoofdstuk 6** stelt een nieuwe aanpak van optimalisatie voor gebaseerd op simulaties met verschillende stadia om het logistieke systeem te optimaliseren in termen van minimale inactieve tijd door gebrek aan beschikbaarheid van ruimte om te storten. Deze aanpak bestaat uit het afwisselend draaien van een deterministisch optimalisatiemodel en een stochastisch simulatiemodel. Dit combineert simulatie, een transportprobleem en een planningsprobleem. Een controle module is gebruikt om verfijningen voor te stellen aan parameters van het optimalisatiemodel na elke iteratie. Dit iteratieve proces eindigt zodra een stop-criterium is bereikt.*

***Hoofdstuk 7** geeft een overzicht van de voornaamste conclusies van deze studie. Verder geeft dit hoofdstuk een lijst aanbevelingen en mogelijkheden voor vervolgonderzoek in de toekomst.*

1

INTRODUCTION

1.1. Background Information

Of the Earth's fossil fuels, coal is the least expensive for its energy content and is the most abundant and widely dispersed energy source. Supplies are readily available and not subject to disruption. At the time of writing, a third of Denmark's electricity and around half of electricity in Germany, Bulgaria, Greece, and the Czech Republic is generated from hard coal and lignite. In Poland, over 80% of electricity generation depends on hard coal and lignite (Eurocoal, 2017). However, burning coal in power plants is a major source of carbon dioxide (CO_2) emissions (World Energy, 2016). In the light of the Paris Agreement and the EU's tough climate targets, coal, oil and natural gas are viewed as transition fossil fuels, because they are ultimately incompatible with a low-carbon, climate-friendly economy. The transition process, in the view of experts, is a long-term task up to year 2050. Thus, coal (hard coal and lignite) will continue to provide a significant contribution to electrical energy supply in Europe during the next decades, supporting the anticipated change towards increasing use of renewable energy sources (Eurocoal, 2017).

During these three to four decades, many steps have to be taken to maintain a secure and affordable power supply while reducing CO_2 emissions and introducing new, but currently unknown technologies. A challenging problem, now, is that due to lower gas prices, generous renewable energy feed-in tariffs, EU-wide CO_2 pricing, national carbon taxes and coal taxes, as well as other measures to reduce greenhouse gas emissions have all weakened coal's market position. Although oil and gas prices recovered to the same levels as in 2015, after dropping at the beginning of 2016, they remained relatively low and therefore competitive against coal. In order to survive as a strong component in Europe's future energy mix, the coal sector puts a strong focus on research and development into the future technologies that will be needed to keep coal in a sustainable and competitive energy mix (Eurocoal, 2017).

A sustainable exploitation of coal deposits is a complex multi-objective problem. Production management aims to maximize utilization and effective production rates of major mining equipment, minimize specific costs, and ensure compliance to the mine's long-term plan. At the same time, the extracted coal has to meet tight specifications of customers; mainly modern coal fired power plants. Customers' requirements are usually in terms of upper and lower bounds of multiple coal quality parameters, such as calorific value, ash, sulfur, which have to be met on a train-by-train basis. Furthermore, the overburden covering the coal has to be excavated, transported, and dumped in a sequence that guarantees safety and long-term stability of the waste dump.

If geological conditions are reasonably constant, coal (lignite) can be extracted from deposits utilizing continuous opencast mining systems. These typically consist of multiple excavators and waste-spreaders, connected by multiple ten-kilometers of belt conveyors. Compared to discontinuous shovel-truck systems, continuous mining is characterized by higher capital expenditures and lower operating expenses leading to a significant proportion of fixed costs. Also, there are strong interdependencies between system constituents, which lead to increased planning requirements.

Material management in such systems is concerned with planning, organizing, and control of the flow of materials from their extraction points to destinations. Its aim is to get the right quality and quantity of materials at the right time and the right place for the lowest cost. Decisions related to material management made in short-term planning include: (i) the extraction sequences of blocks, (ii) the destination of extracted material and (iii) the extraction rate of excavators.

Optimal decision making and production control is impacted by uncertainty associated with the incomplete knowledge of the deposit. This originates from the nature of exploration and grade control stage, were the deposit and its attributes of interest are spatially sampled at some locations. A residual uncertainty remains in-between the exploration data location. The uncertainty in such deposits can be quantified by geostatistical simulation methods. Geostatistical simulation often is preferable to traditional interpolation approaches such as Kriging, in part because it captures the heterogeneous character observed in many deposits. Geostatistical simulation methods preserve the variance observed in the data, instead of just the mean value, as in interpolation. Their stochastic approach allows calculation of many equally probable solutions (realizations), which can be post-processed to quantify and assess uncertainty.

Another source of uncertainty originates from unscheduled breakdowns of equipment. Maintenance efforts are rather sophisticated and lead to technical availabilities of single system components up to 95% to 98%. However, the interconnected nature of the system results in deviations from the expected system performance. The combined availability of two components in series is always lower than the availability of its individual components. The system reliability decreases very rapidly as the number of series components increases (Billinton and Allan, 1992). In fact, the ability to reach short-term targets in terms of coal quantity and quality is influenced by unexpected failure of equipment, which are planned to contribute to a coal product mix. Statistical techniques can be used to fit a theoretical distribution to historical failure data. This would enable us to predict the probability or forecast the frequency of occurrence of the failure in a certain interval.

The complex interaction between the aforementioned objectives, all mining elements, and the deposit model does not allow formulating a closed form optimization problem to find optimum or good decisions. Optimization methods, especially those that are applied in real-world problems, formulate the decision problems into mathematical models. They tend to oversimplify the dynamics and the stochasticity of the real system. Hence, an alternative approach needs to be explored.

Supply chain management, manufacturing environments, etc. deal with the very same problem (Jung et al., 2004, Truong and Azadivar, 2003). The differences might be the size and the type of decisions that have to be made. Stochastic process simulation alone and in some cases combined with optimization has been prominently used in these fields to assist the decision making process (April et al., 2003, Fu et al., 2005, Subramaniam and Gosavi, 2007). In most cases, simulation models only function as system analysis tools. In the context where decisions have to be made to obtain pre-defined objectives, simulation studies help to perform the computational experimentation. Prior to the decision making, assessments can be performed on pre-defined decision alternatives considering these objectives. In other words, feasible solutions can be explored using what-if analyses and among these solutions the best decision can be found (Zeigler et al., 2000). These analyses are normally performed in an iterative routine. Results of previous experiments are used to perform following experimentations. In summary, the assessments against forthcoming uncertainties are used to make representative decisions. The only drawback here is that it requires additional effort from the decision maker to come to the best decisions (Halim and Seck, 2011).

Considering the drawback in simulation studies, optimization techniques can clearly help by providing the structure required to achieve the best decisions. The search process of finding the best decisions can be automated, if the optimization method is implemented in a computer program. In fact, the reported successful efforts in combining simulation and optimization methods encourage the development of research into this so-called simulation-based optimization field. In the simulation-based optimization method, optimization performs as the search method that discovers the alternative space of a simulation model in such a way that solutions contributing to the desired system performance(s) can be found (Halim and Seck, 2011). Figure 1.1 depicts the concept of this method.

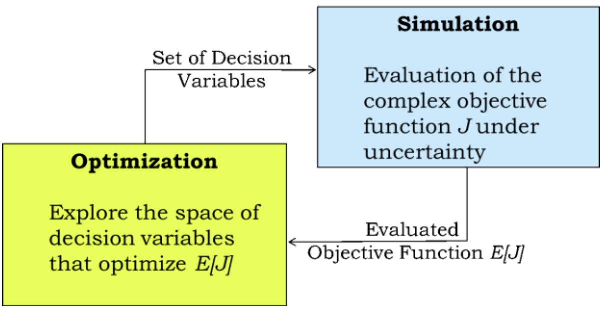

Figure 1.1. Simulation-based optimization method (adapted from (Gosavi, 2003)).

Using this method, optimal solutions can be obtained from the modeled mining system without tiresome effort (manually going through the whole set of feasible alternatives for the input of the simulation model) while the dynamics and stochasticity of the system are taken into account.

At the time of writing, the simulation-based optimization method in its entirety has not been applied in the coal mining industry. Little research to date has focused on the application of simulation modeling as a powerful operational decision support in material management. In addition, most of the studies have simplified their case studies to solve one particular question. Practical experiences from implementing the simulation-based optimization method for the decision making at an industrial scale application are not known to the author.

1.2. RESEARCH OBJECTIVES

This research aims to

"Develop a stochastic mine process simulator capturing different sources of uncertainty, including geological uncertainty, unscheduled breakdowns of equipment, and their interdependencies" and "propose a new simulation-based optimization algorithm applicable to short-term production scheduling of opencast mines".

To achieve these goals, the following objectives were formulated:

1. Investigate available process simulation and simulation-based optimization techniques and find the appropriate approach based on characteristics of the problem under study.

2. After the selection of the suitable method, develop an algorithmic approach to simulate the process of continuous mining systems. The approach includes a formal description of stochastic simulation in such systems.

3. Once the algorithmic approach is developed, investigate the usability of simulation techniques for decision support under geological uncertainty and stochastic breakdown behavior of major equipment. Explore a suitable computational approach for integrating two types of simulations. In particular, consider Monte-Carlo simulation techniques in geostatistics for modeling uncertainty associated with deposit models and Discrete Event Simulation (DES) methods allowing for stochastic process modeling under uncertainty.

4. Conduct an extensive experiment in a synthetic, completely known, and fully controllable environment to validate the simulation model and to evaluate its performance. This allows benchmarking against the 'ground-truth'. In this stage, TRL 4 (more details can be found in appendix A) will be achieved.

5. After the implementation in the lab environment, set up the simulation process for a field test in an actual mining operation and validate results at an industrial scale; TRL 6 will be achieved.

6. Once the simulation model is successfully validated, develop a new multi-stage simulation-based optimization approach for the short-term scheduling problem of continuous mining systems. Investigate a solution strategy that is capable of optimizing dispatch decisions for given extraction sequences while ensuring the construction of a stable dump.

7. Apply the simulation-based optimization approach in an actual mining operation. Design a heuristic control module that analyses the output of the simulation model and suggests new input parameters for the optimization block. The module should be specifically tailored to the problem under study.

1.3. Thesis Outline

The outline of this dissertation is organized in a way that covers the previously formulated research objectives. It is divided into seven chapters as follows:

Chapter 2 provides a detailed problem specification of the case studies. In this dissertation, the performance of the developed concepts will be demonstrated in two different real-size case studies. Complete descriptions of the case studies together with the challenges and problems are presented.

Chapter 3 presents a literature review of stochastic simulation and simulation-based optimization. Furthermore, it provides a brief theoretical background of the developed algorithmic approach for the simulation modeling of continuous mining systems. A formal description of the stochastic simulation of opencast mines can be found in this chapter. This chapter further discusses a set of steps that should be followed in a simulation study as well as the possibilities of coupling the simulation to the optimization. The last section presents a simulation-based optimization platform, which will be used for the optimization of the short-term scheduling problem of continuous mining systems.

Chapter 4 presents the synthetic experiment in a fully controllable environment. It demonstrates that the developed concept is capable of quantifying the effects of geological uncertainty, unscheduled downtimes, and their impacts on the ability of delivering contractually defined coal quantities and qualities.

Chapter 5 extends the developed simulation model in the previous chapter to a new level by implementing it in an industrially relevant environment. A framework for modeling, simulation, and validation of the simulation model of a large continuous mine is presented in detail. The chapter further discusses operational implementation issues, experiences, and challenges in practical applications. Furthermore, the strength of the application of the simulation modeling as an operational decision support for material management in continuous mining systems is demonstrated. Results of both case studies are used to describe the details of the framework, and to illustrate the strength and limitations of its application.

Chapter 6 proposes a new multi-stage simulation-based optimization approach. This approach consists of running alternatingly a deterministic optimization model and a stochastic simulation model. After an introduction, the first subsection provides a brief background to the production planning of continuous mining systems. It continues by defining the problem. The third subsection discusses the solution strategy, which is a combination of the simulation, the transportation problem, and the job-shop scheduling problem. Thereafter, the computational framework and its implementation are presented. The Hambach mine (Case 2) is used to demonstrate the performance of the proposed approach. Subsequently, the obtained results are discussed in detail. The last subsection concludes the findings of the chapter.

Chapter 7 is the last section of this dissertation and gives an overview of the main conclusions from this study. The chapter further provides a list of recommendations and future research possibilities.

2

PROBLEM SPECIFICATION

The contents of this chapter have been adapted from:

Shishvan, M. S., & Benndorf, J. (2017). Operational Decision Support for Material Management in Continuous Mining Systems: From Simulation Concept to Practical Full-Scale Implementations. *Minerals, 7*(7), 116. doi: 10.3390/min7070116

2

2.1. INTRODUCTION

In this dissertation, the performance of the developed concepts will be demonstrated in two different real case studies. Both case studies are located in Germany and their main product is lignite (often referred to as brown coal). Lignite is a soft brown combustible sedimentary rock formed from naturally compressed peat. It is considered the lowest rank of coal due to its relatively low heat content. It has a carbon content around 60–70 percent. It is mined all around the world and in Germany is used almost exclusively as a fuel for steam-electric power generation (Stoll et al., 2009).

Lignite production in Germany is centered in four mining areas, namely (i) the Rhenish mining area around Cologne, Aachen, and Mönchengladbach, (ii) the Lusatian mining area in southeastern Brandenburg and north-eastern Saxony, (iii) the Central German mining area in the south-east of Saxony-Anhalt and in north-west Saxony, as well as (iv) the Helmstedt mining area in Lower Saxony. In these four mining areas, lignite is exclusively extracted at opencast mines. In 2015, 178.1 million tonnes of lignite was produced. To produce this much of lignite, 887.8 million m^3 of overburden were moved during mining – an average overburden-to-coal ratio of 5.0 cubic meters per tonne (Eurocoal, 2017). The first case study concerns the Profen mine from the Central German mining area and the second one concerns the Hambach mine from the Rhenish mining area.

Figure 2.1 shows a schematic section view of a continuous mining system. The operation starts with the excavation of materials by excavators (supply points) at the extraction side. It continues by the transportation of the extracted materials from

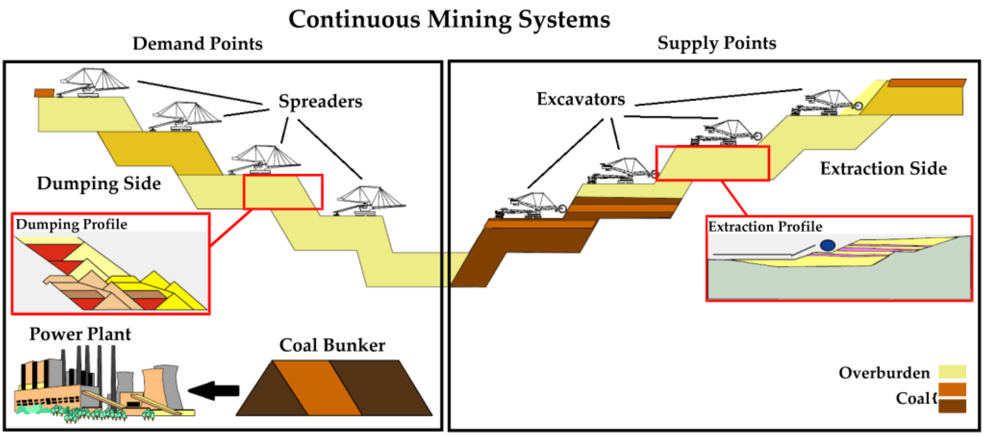

Figure 2.1. A schematic view of continuous mining systems, reproduced after (Gärtner et al., 2013).

mining benches to dumping benches or a coal-bunker. The transportation process includes a network of belt conveyors consisting of face conveyor belts, main conveyor belts, and a mass distribution center. Finally, lignite is stacked at the bunker or waste materials are dumped at the dumping site (demand points).

2.2. CASE STUDY - 1: THE PROFEN MINE

2.2.1. CASE DESCRIPTION

The Schwerzau mining field of the Profen mine is used as an industrial case study for developing the stochastic mine system simulator. It is operated by Mitteldeutsche-Braunkohlengesellschaft mbH (MIBRAG). The Schwerzau mine field commenced production in 2006. The mine has coal reserves amounting to 115 million tons of lignite. Continuous mining equipment (bucket wheel and chain excavators) will ultimately mine lignite in six combined overburden and coal cuts.

In general, continuous mining systems for the extraction of lignite contain parallel production lines, which start with Bucket Wheel and/or Bucket Chain Excavators (BWEs/BCEs) followed by material transport by conveyor belts. Material is distributed at the mass distribution center, where several destinations can be chosen, including the coal-bunker and different spreaders at the waste materials dumping site. Waste is dumped by spreaders at the dump site and lignite is stacked by the stacker in the stockpile. A reclaimer at the stockpile and a system of conveyors, screens and crushers are used for loading lignite in the train cars. Finally, these trains are sent to customers, mostly power plants, based on their daily demands. A schematic view of the extraction system of the Profen mine is shown in Figure 2.2.

It consists of six excavators, two spreaders, and a coal-bunker. An overview of specifications of the equipment can be found in Table 2.1. The excavators have to be scheduled with the following operation details:

- The excavator Bg. 1580 extracts only waste (sand, gravel, and clay) and is connected to the spreader Abs. 1104.
- The excavators Bg. 1511 and Bg. 1553 can send the extracted materials to the all defined destinations, (the coal-bunker, the spreaders Abs. 1112, Abs. 1104).
- The excavators Bg. 351, Bg. 1541, and Bg. 309 extract coal and waste and have access to the spreader Abs. 1112 and the coal-bunker.

2

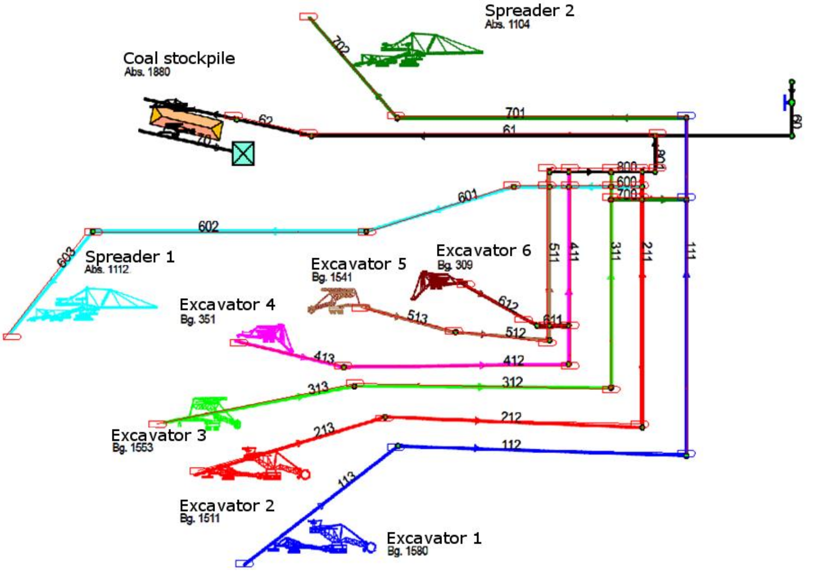

Figure 2.2. Schematic overview of the production system in the Profen mine.

Table 2.1. An overview of the specifications of the equipment.

Exc. Model	Bench	Access to Abs. 1112	Access to Abs. 1104	Access to Coal-bunker	Theoretical Capacity (m^3/h)
Bg. 1580	1	No	Yes	No	4900
Bg. 1511	2	Yes	Yes	Yes	4900
Bg. 1553	3	Yes	Yes	Yes	3770
Bg. 351	4	Yes	No	Yes	1400
Bg. 1541	5	Yes	No	Yes	3770
Bg. 309	6	Yes	No	Yes	740
Abs. 1112	-	-	-	-	10,000
Abs. 1104	-	-	-	-	10,000

2.2.2. Case Problem

In this case, challenges originate from geological uncertainty associated with the detailed knowledge about the coal deposit as well as from unscheduled break-downs of equipment as an internal factor. As an illustration, Figure 2.3 shows the difficult geology in the Profen mine that affects the deliverable coal quality and quantity. Yueksel et al. (2017) quantify geological uncertainty of the deposit using conditionally simulated realizations. They apply the Sequential Gaussian Simulation method (SGS) to create the realizations.

Figure 2.3. Complicated geology in the Profen mine (second bench).

This dissertation uses their output result as the reserve block model. It includes an average type estimated model using Ordinary Kriging and 25 realizations of the deposit.

Three different coal types including power plant coal 1 (KK1), power plant coal 2 (KK1), and dust coal (SK) can be extracted in the Profen mine. The features of the different coal types are given in Table 2.2. Coal quality control is performed via an online sensor measurement (RGI) and lab analysis. The online sensor is located on conveyor 61 and measures ash and water content on a minute time interval. The most accurate measurement is done in a laboratory on samples that are taken from train cars leaving the stock/blending yard toward customers.

Table 2.2. Coal types and their properties.

Coal Type	Ash Content (%)	Calorific Value (MJ/kg)
KK1	<8.5% (wet ash)	9.5–10.5
KK2	<12% (wet ash)	9.0–11.4
SK	<15% (dry ash)	>24.5

To emphasize the effect of geological uncertainty, Figure 2.4 shows historical data about the ash content of delivered trains to a power plant. As can be seen, there are three different values; the average value of extracted blocks based on the estimated block model (magenta line), the online sensor measurement (blue line), and the laboratory measurement (green line). The lab measurements (which are called the reality in this dissertation) show a significant fluctuation compared to the estimated model. In addition, systematic deviations over longer time spans can be detected. These observations emphasize the necessity of accounting for geological uncertainty when forecasting the coal quality by the mine simulator.

2

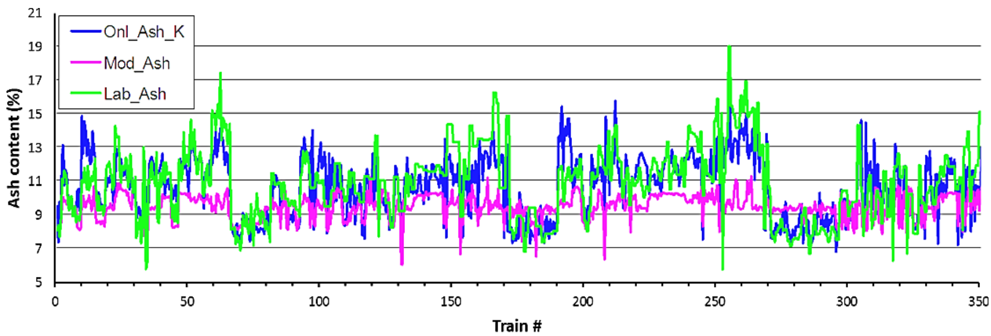

Figure 2.4. Historical data of ash content of delivered trains to the power plants (provided by MIBRAG).

An understanding of the frequency and magnitude of deviations to be expected already at the planning stage would help the planning engineer to achieve better and more robust decisions. In addition, due to the complex nature of the problem involving multiple targets, a fast evaluation tool for the short-term planner and operations personnel would facilitate evaluating alternative decision scenarios fast and best decision making. Thus, the defined test case focuses on controlling the contractually defined coal quantities and qualities. In this dissertation, an integrated simulation as a solution approach is suggested.

2.3. Case Study - 2: The Hambach Mine

2.3.1. Case Description

2

The second case study is the Hambach mine; it produces over 40 million tons of coal and over 250 million m^3 of overburden materials per year. A schematic view of the Hambach mine is shown in Figure 2.5. In total eight BWEs have to be scheduled to serve continuously seven spreaders with waste material and two bunkers with coal. Table 2.3 shows the technical specifications of the BWEs. Each BWE excavates either lignite or waste in terrace cuts and transfers materials to the face conveyor belt, which carries it along the bench to the main conveyor belt. All excavated materials of the eight benches are distributed to their destinations at the mass distribution center. Based on a predefined daily schedule, waste is distributed to the seven spreaders for dumping, and lignite is forwarded to two coal-bunkers.

The mine operates 24 hours per day and seven days per week. Regular maintenance is carried out on weekly, monthly, and annually based schedules. During the regular maintenance or an unscheduled breakdown, the production process ceases on the bench.

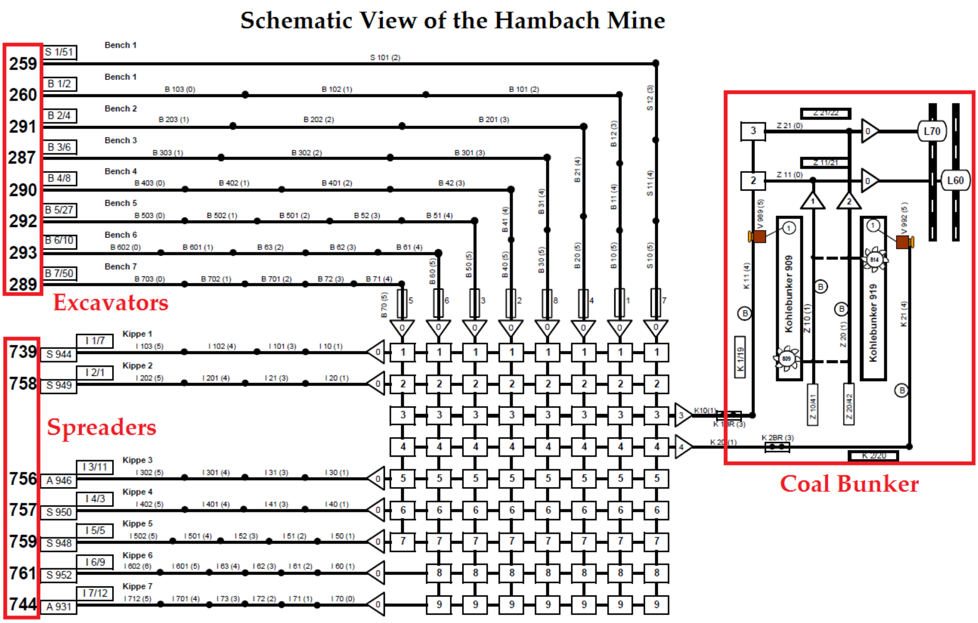

Figure 2.5. Schematic overview of the production system of the Hambach mine.

Table 2.3. Technical specification of BWEs.

Bench	BWE Model	Discharge Per min	Bucket Capacity (m^3)	Theoretical Capacity (m^3/h) *
S1	259	44	2.6	5700
B1	260	38	3.5	5700
B2	291	48	5.0	12,500
B3	287	43	5.1	10,400
B4	290	48	5.0	12,500
B5	292	48.6–72.0	5.0	12,500
B6	293	48.6–72.0	5.0	12,500
B7	289	48	5.0	12,500

* 19.3 h per day

2.3.2. Case Problem

Waste materials at the Hambach mine are categorized in three types of mixed soils, dry mixed soils type1 (M1), semi-wet mixed Soils type2 (M2T) and wet mixed soils type2 (M2N). The extraction of M2 type materials is increasingly facing deficiencies in output due to difficult mining materials. This type of soil, specifically M2N, exhibits a high share of cohesive components and is difficult to drain. M2N material cannot be used for stable dump construction and needs to be filled in between prebuilt polders constructed of dry material (see Figure 2.6). The fact that only a limited quantity of these unstable mixed soils can be placed in the waste dump causes downtimes and bottlenecks in the placement process on the dumping side.

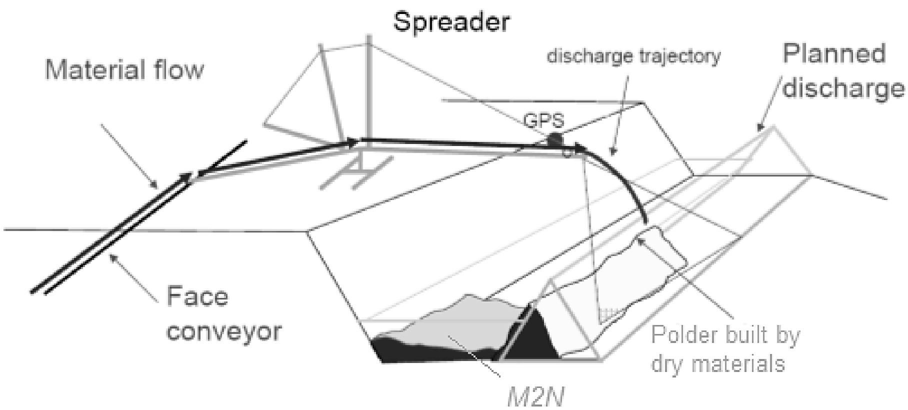

Figure 2.6. Placement of M2N materials in between a prebuilt polder, (Gärtner et al., 2013).

Furthermore, historical data show that next to scheduled maintenance, breakdowns of the equipment occur in a random manner. Due to the "in series" system configuration, equipment units feeding or connected to the ceased equipment are blocked and set out of the operation while the maintenance is being done or the failure is being repaired. Furthermore, because of the multi-layer nature of the deposit, changes from one material type (e.g., M1) to another material type (e.g., M2N) happen very frequently. Each time a material change takes place, the BWE stops excavating while the mass distribution center changes the drop-point of the belt conveyor to its new destination. In reality, this operation approximately takes five to eight minutes. This time may increase due to the unavailability of the new destination. The combined effect of random equipment breakdowns and frequent changes in extracted materials makes the prediction of the exact material flow rate at any given future time span a major source of uncertainty. Thus, the problem is a constrained stochastic optimization problem.

The objective is to optimize dispatch decisions to decrease downtimes/increase efficiency of excavators and spreaders by effective resource allocation while ensuring stable dump construction. In this dissertation, a simulation-based optimization approach is suggested as a solution strategy.

3

METHODOLOGICAL APPROACH

The contents of this chapter have been adapted from:

Section 3.2, Section 3.3, and Section 3.6:

Shishvan, M. S., & Benndorf, J. (2014). Performance optimization of complex continuous mining system using stochastic simulation. Paper presented at the Engineering Optimization IV, LISBON, PORTUGAL.

Benndorf, J., Yueksel, C., **Shishvan, M. S.**, Rosenberg, H., Thielemann, T., Mittmann, R., Donner, R. (2015). RTRO–Coal: Real-Time Resource-Reconciliation and Optimization for Exploitation of Coal Deposits. Minerals, 5(3), 546-569.

Shishvan, M. S., & Benndorf, J. (2016). The effect of geological uncertainty on achieving short-term targets: A quantitative approach using stochastic process simulation. Journal of the Southern African Institute of Mining and Metallurgy, 116(3), 259-264.

Section 3.1, Section 3.4, and Section 3.5:

Shishvan, M. S., & Benndorf, J. (2017). Operational Decision Support for Material Management in Continuous Mining Systems: From Simulation Concept to Practical Full-Scale Implementations. *Minerals*, *7*(7), 116. doi: 10.3390/min7070116.

Section 3.7, Section 3.8, and Section 3.9:

Shishvan, M. S., & Benndorf (2017). A Simulation-based Optimization Approach for Material Dispatching in Continuous Mining Systems. Under review at European Journal of Operational Research (EJOR).

3.1. INTRODUCTION

In this dissertation the terms system, model, and simulation will be used. To guide the reader, upfront definitions and explanations are provided.

A system is defined to be a collection of entities that act and interact together toward the achievement of some logical end. This definition was proposed by Schmidt and Taylor (1970). In practice, what is meant by "the system" depends on the objectives of a particular study.

Modeling is the process of producing a simplified representation of a complex system of interest. Such a simplified version of a system is called a model. A model constructs a conceptual framework that describes a system and enables the analyst to predict the effect of changes to the system (Maria, 1997). Modeling is a constructive activity and the challenge is to capture all relevant details and to avoid unnecessary features. This raises the natural question of whether the model is good enough from the point of view of the requirements implied by the project goals (Birta and Arbez, 2013).

A simulation is the imitation of the system's operation. It is used to answer What-if-questions. It can be used before an existing system is changed or a new system built, to reduce the chances of failure to meet specifications, to eliminate unforeseen bottlenecks, to prevent under or over-utilization of resources, and to optimize system performance (Maria, 1997).

A simulator can be introduced as a device that replicates the operational features of some particular system. The fundamental requirement of any simulator is the replication (Birta and Arbez, 2013).

In general, a model intended for a simulation study is a mathematical model. Mathematical model classifications consist of deterministic (input and output variables are fixed values) or stochastic (at least one of the input or output variables is probabilistic); static (time is not taken into account) or dynamic (time-varying interactions among variables are taken into account), Figure 3.1. Typically, simulation models are stochastic and dynamic (Kelton and Law, 2000). Based on a system specification formalism, Kelton and Law (2000) categorized dynamic models into two types, discrete and continuous. A discrete model changes instantaneously in response to certain discrete events. A continuous model is based on differential equations and attempt to quantify the changes in a system continuously over time in response to controls. From now on, the term model refers to the stochastic discrete model (the highlighted box in Figure 3.1). The next section reviews literature on stochastic simulation and its applications.

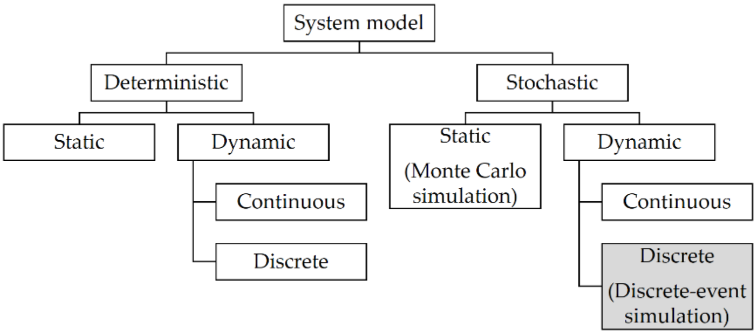

Figure 3.1. System model taxonomy (reproduced after Kelton and Law (2000)).

3.2. State of the Art in Stochastic Simulation

The usability of two particular simulation methods will be investigated within this dissertation including geostatistical simulation and discrete-event simulation (DES). This section reviews recent developments documented in literature for both. Concluding gaps are identified and the progress beyond state-of-the-art within this chapter defined.

3.2.1. Geostatistical Simulation for Lignite Deposits

Estimated models, such as generated by inverse distance weighting or Kriging, describe the spatial distribution of coal attributes and can be considered to be good locally. However, they also exhibit a smoothing effect and do not offer realistic uncertainty measures. To account for variability and grade uncertainty, methods of conditional simulation have increasingly been applied in geostatistical modeling over the last two decades (Chiles and Delfiner, 2012, Dimitrakopoulos, 1998, Srivastava, 2013). Conditional simulation is a Monte-Carlo-Simulation-based technique that allows for generating multiple possible models or scenarios of the deposit based on the information available, usually exploration drill holes. Each model is called a realization; it reproduces available data and information, statistics and spatial variability. In terms of geostatistics, the generated models reproduce the representative data histogram and the variogram. A commonly used method for generating these models is Sequential Gaussian Simulation (SGS) (Goovaerts, 1997). Recently, a method was introduced to update coal quality models based on online senor data, which allows to decrease uncertainty of prediction significantly (Wambeke and Benndorf, 2017, Yueksel et al., 2017).

Figure 3.2 shows a comparison between models generated by interpolation and simulation for a multi-seam coal deposit (Benndorf, 2013a). A visual inspection of the models illustrates the differences very well. The interpolated model suggests a very smooth seam geometry and distribution of calorific value; however, this smoothness does not represent what was found in the data. Essentially, this smooth behavior does not represent reality. The two simulated models exhibit features inferred from data, namely the variability. Each realization captures the global structure of the deposit but exhibits a different behavior at a local scale.

Analyzing the spread of values from different realizations at a location, say a mining block, allows for quantifying uncertainty in prediction and inferring probabilities of exceeding certain thresholds. Various case studies about the value added when using conditional simulation techniques in coal mining, in particular in resource/reserve evaluation and long-range planning, are documented in the literature (e.g. (Costa et al., 2000, Jurek et al., 2013, Falivene et al., 2014, Naworyta et al., 2015));

The focus of this dissertation is rather on discrete-event simulation and the integration with geostatistical simulation. Dowd and Dare-Bryan (2005) explored the general concepts of the integration of geostatistical simulation within the entire design and production cycle. The authors illustrated these concepts with particular reference to blast modeling. For the latter, the interested reader will find more detailed information in the mentioned literature references.

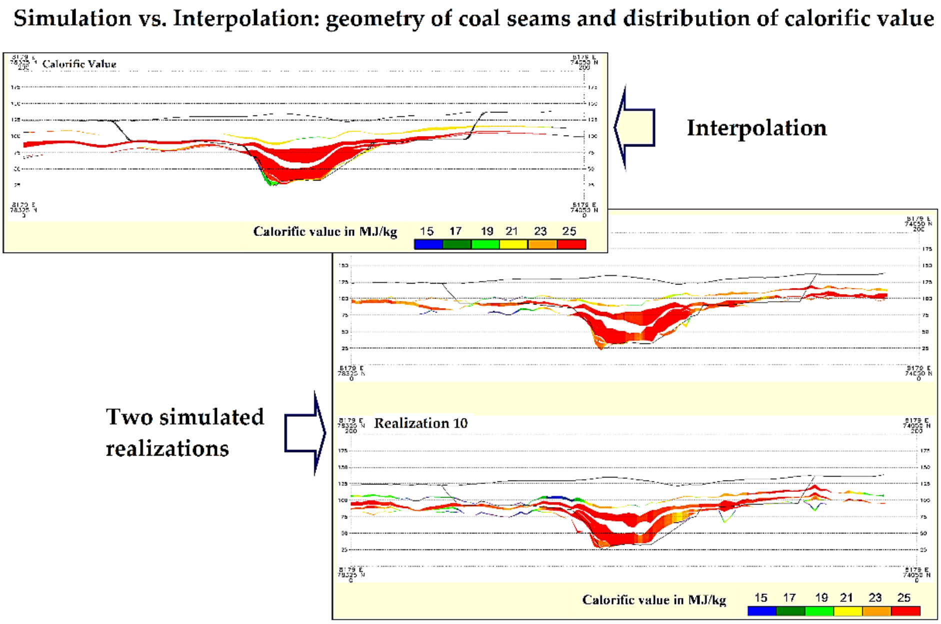

Figure 3.2. Comparison between deposit models based on interpolation and simulation in geostatistics (Benndorf, 2013)

3.2.2. The Use of Discrete-Event Simulation for Mining Systems

Techniques of stochastic process simulation, whether discrete, continuous or combined, are stated to provide a powerful tool for measuring performance indicators of complex systems associated with some sort of randomness (Kelton and Law, 2000). In the past decades, there has been a large development in applications of process simulation in the mining industry. Manula and Rivell (1974) attempted to develop a comprehensive model of a coal mine taking into account the environmental, geological, material handling, support and other sub-systems. The result was the simulation program Under-ground Generalised Materials Handling System (UGMHS). The objective of their model was to study the behaviour of the system to gain insight into the problem of safety and productivity and validate experimental conclusions. Michalopoulos and Topuz (1985) used an event-oriented model to simulate mines that are operating with the long-wall method. The model deals with coal mining machines, transportation system, and roof support units. Failures of equipment were taken into account. Lebedev and Staples (2002) demonstrated the application of simulation modeling for designing the entire material handling system of a new underground mine using commercial simulation software. Salama et al. (2013) studied a combination of discrete event simulation and Mixed Integer Programming (MIP) as a tool to improve decision making in underground mining. The proposed method uses the simulation approach to evaluate the operating costs of different haulage system scenarios. The cash flows generated assessing different scenarios are the input into the MIP model. Baafi and Ataeepour (1996), Jaoua et al. (2012), Askari-Nasab et al. (2012), Askari-Nasab et al. (2014) use discrete event simulation to investigate a truck-shovel system of discontinuous open pit mines. The process simulation method is used to optimize the truck fleet size for the system. Only a few studies have been done in the field of continuous mining systems. Panagiotou (1983) describes the application of the simulation program SIMPTOL for opencast lignite mines that use BWEs, conveyors and stackers. The main objective is to select and match the equipment to fit material characteristics while meeting production requirements and mine profiles. Michalakopoulos et al. (2005) present the simulation model of an excavation system at a multi-level terrace mine using the GPSS/H simulation language. The principal model output variables are production and arrival rate at the transfer point of mineral and waste. Fioroni et al. (2007) apply discrete tools for simulation of continuous behavior for modeling of the conveyor belt network in a large steelmaking plant. The authors proposed a modeling approach of the flow process in which portions of materials are treated as discrete entities in simulation modeling. The results demonstrated that this technique was valid and successful. Roumpos et al. (2014) applied process simulation to estimate the initial belt conveyor system exiting point on the mine perimeter. This rough estimation is used together with an optimization algorithm to find the optimal location of the distribution center of the belt conveyor system in continuous mining systems. Later on Michalakopoulos et al. (2015) utilized a commercial simulation software to simulate the Kardia Field mine in Greece. Validation of the results illustrates an acceptable agreement with the actual data.

3.2.3. Analysis of Literature & Progress within the State-of-the-Art

The reviewed literature demonstrated that stochastic process simulation can be successfully used as decision support during equipment selection, system design and mine planning. In the above applications, estimated deposit models were used as input ignoring geological uncertainty. The investigation of the impact of geological uncertainty on the performance of continuous mining systems in combination with random system breakdowns has not yet been studied in detail. To account for this gap, Chapter 4 presents a new stochastics-based mine process simulator focusing on the effects of geological uncertainty and unscheduled breakdowns of equipment. Furthermore, among these studies, little research to date has focused on the application of simulation modeling as a powerful operational decision support tool in material management. To the best of our knowledge, there are no comprehensive works in bridging simulation concept to the practical implementation in large continuously operating mines. This gap will be investigated in Chapter 5.

Next, a formalized description of the simulation approach is provided. Then, steps of a simulation study are discussed. The verification and the validation steps are elaborated in more detail.

3.3. Formal Description of Stochastic Simulation in Continuous Mining Systems

As stated in the second research objective, an algorithmic approach should be developed. The following presents the developed formal description of stochastic simulation in continuous mining systems. After a declaration of variables, the focus is on describing general Key Performance Indicators (KPIs) for continuous mining systems, which will be used to evaluate different planning variants. Decision and control options for short-term mine planning and production control are explained. The link between KPIs and operational decisions is complex and may not be explicitly described by an analytical relation, in particular when the interest is in uncertainty (Gosavi, 2003). This link will be provided by the discrete-event mining process simulation combined with geostatistical simulated deposit models. First, sets and indices are defined.

Sets

8. N : set of key performance indicators, *KPIs;*
9. T : set of extraction periods;
10. MT : set of types of materials;
11. Q: set of critical coal quality parameters;
12. E : set of excavators;
13. R : set of simulation replications.

Indices

14. $t \in T$: index of mining periods, $\{1, 2, 3, \ldots, T_{max}\}$;
15. $mt \in MT$: index of types of materials, $\{1, 2, 3, \ldots, MT_{max}\}$;
16. $q \in Q$: index of coal quality parameters, $\{1, 2, 3, \ldots, Q_{max}\}$;
17. $e \in E$: index for excavators, $\{1, 2, 3, \ldots, E_{max}\}$;
18. $n \in N$: index for *KPIs*, $\{1, 2, \ldots, N_{max}\}$;
19. $r \in R$: index of simulation replications, $\{1, 2, \ldots, R_{max}\}$.

3.3.1. Evaluation Function

The simulation approach is designed to quantify a value representing the level of achievements towards several defined targets. This value will subsequently be called the evaluation function value, Equation (3.1). Since there are multiple objectives, a representative value can be obtained by summing up the weighted system KPIs, which are defined hereafter. The weights indicate the importance of the corresponding KPI; they can be adjusted by the user as required.

$$J = \frac{1}{R_{max}} \sum_{r \in R} \sum_{t \in T} \sum_{n \in N} C_{nt} \cdot J_{nt}^{r}, \tag{3.1}$$

where, J_{nt}^{r} is the merit of the n^{th} KPI at time t and replication r and C_{nt} represents the related weight. To incorporate the effect of stochastic components, the evaluation function is evaluated as a mean value over a set of replication R. Alternatively, a distribution of the evaluation function can be derived by calculating a histogram from values corresponding to different replications.

A different approach for evaluating a certain outcome of a simulation model run with respect to multiple KPIs is to use the Pareto concept (e.g. Branke et al., 2008). The outcome defines a Pareto point in an N_{max} - dimensional space, which can be compared to other outcomes based on other decision variables by means of a Pareto frontier. This way of multi-objective evaluation can be of particular interest for finding better decision variables using simulation-based optimization. It is not further discussed in this dissertation.

3.3.2. Key Performance Indicators, KPIs

KPIs should be defined to measure process performance with respect to previously defined objectives or targets. Generally, for production control of continuous mining systems, meeting the coal quality and quantity targets, compliance with the long-term plan, effective capacity, specific energy usage, or utilization of the equipment can be of interest to the mining industry. In this contribution, the focus is on three of these KPIs: meeting the coal quality targets, the coal quantity targets, and utilization of equipment. These will be described in detail in the next sub-section.

3.3.2.1 Coal Quality KPI

Meeting quality specifications of coal is most critical in lignite extraction. To reach high efficiencies in the downstream processes, e.g. high efficiency in the power plant, multiple coal quality parameters have to be delivered within predefined target ranges. These coal quality parameters can include the calorific value, ash content, sulfur content, iron (Fe_2O_3) content in the ash, or moisture of the coal. Deviating from these targets may result in costs. To evaluate a short-term mine plan with respect to coal quality, a penalty function is introduced quantifying this KPI, which associates a cost to deviations from upper or lower coal quality limits.

Equation (3.2) defines the KPI related to penalties for deviating from minimum and maximum values of quality targets for different types of extracted materials. It sums up all deviations from production targets over all defined time periods t, for all coal products mt for a replication r.

$$J_{1t}^{r} = \sum_{mt \in MT} \sum_{q \in Q} \begin{bmatrix} max\left(0, \left(CQ_t^{q,mt,r} - TQ_{max,t}^{q,mt}\right)\right) Cd_{q,u}^{mt} \\ +max\left(0, \left(TQ_{min,t}^{q,mt} - CQ_t^{q,mt,r}\right)\right) Cd_{q,l}^{mt} \end{bmatrix} CT_t^{mt,r}, \qquad (3.2)$$

$$for\ t = 1, \dots, T_{max}, \mathrm{r} = 1, \dots, R_{max},$$

where, $CT_t^{mt,r}$ is the coal tonnage of product mt in tons, mined in period t and related to replication r, and $CQ_t^{q,mt,r}$ represents the coal quality parameter q of product mt in grade units, mined in period t and related to replication r. Both are evaluated by the simulator for each replication. The simulator provides the link between the set of chosen decision variables and the tonnage and quality produced by evaluating the whole extraction process mapped in the discrete-event simulation model.

$TQ_{max,t}^{q,mt}$ and $TQ_{min,t}^{q,mt}$ are maximum and minimum target values of coal quality parameter q of product mt, mined in period t in grade units, and $Cd_{q,u}^{mt}$ and $Cd_{q,l}^{mt}$ are costs related to deviations from upper and lower quality targets in €/(grade unit and ton) for material type mt at time t and replication r. These parameters are defining the penalty function, which can be for example part of a contract between the mine and the customer.

3.3.2.2 *Coal Quantity KPI*

Contractually defined quantities of coal to be delivered have to be ensured on a day-by-day basis. Even when having a stockpile as a buffer, on a day-by-day basis production targets should be met. For a given replication *r*, Equation (3.3) quantifies deviations from coal quantity targets and is designed to evaluate if the quantity of different types of coal extracted in period *t* is within predefined ranges of targets. If not, penalties apply:

$$J_{2t}^{r} = \sum_{mt \in MT} \begin{bmatrix} max\left(0, \left(CT_t^{mt,r} - TT_{max,t}^{mt}\right)\right) Cd_{t,u}^{mt} \\ + max\left(0, \left(TT_{min,t}^{mt} - CT_t^{mt,r}\right)\right) Cd_{t,l}^{mt} \end{bmatrix} CT_t^{mt,r}, \qquad (3.3)$$

$$for\ t = 1, \dots, T_{max}, r = 1, \dots, R_{max},$$

where, $CT_t^{mt,r}$ (tonnes) is coal tonnage related to replication *r*, ($TT_{min,t}^{mt}$, $TT_{max,t}^{mt}$ (tonnes)) are the minimum and maximum of target tonnage and ($Cd_{t,u}^{mt}$, $Cd_{t,l}^{mt}$ (€/tonne)) are the costs of deviation from the target tonnage for upper and lower values of material type *mt* at time *t* and replication *r*.

3.3.2.3 *Utilization KPI*

A representative measure of the extraction system's utilization can be derived from the utilization of excavators (Equation (3.4)). This is because excavators are always located at the first point in the production chain. If any subsequent element of the system is broken down, they stop operating.

$$J_{3t}^{r} = \sum_{e \in E} \left[1 - \frac{T_{active}^{e,t,r}}{T_{scheduled}^{e,t}}\right], \qquad for\ t = 1, \dots, T_{max}, \mathrm{r} = 1, \dots, R_{max}, \qquad (3.4)$$

where, $T_{active}^{e,t,r}$ (hours) is the actual producing time, $T_{scheduled}^{e,t}$ (hours) is the scheduled time. In this way, J_{3t}^{r} provides an average percentage deviation from scheduled operating time, considering all excavators. In case of different weighting of excavators due to different priority, a corresponding weighting factor could be introduced. The difference between actual producing time and scheduled time may be caused by:

- movements of equipment and positioning (changing slices or blocks to extract),

- dispatching purposes, such as changing the destination at the mass distribution center, or
- unscheduled breakdowns.

The first item is an operational requirement and may be estimated with a reasonable accuracy. The second item is directly linked to geological uncertainty and accounts for the fact that different material has to be transported to different destinations. The dispatching action induces a delay since the conveyor configuration has to be changed. If we would know the geology perfectly, then this type of delay could be quantified with 100% certainty prior to operation. The third item, unscheduled breakdowns, is related to uncertainty that is associated with operational behavior of equipment.

3.3.3. Constraints

Every mining operation faces a number of technical and physical constraints. For the presented approach, these are directly applied in the simulation model and are not discussed in detail. However, with respect to the extraction sequence in continuous mining, one special constraint will be stated, which is an addition to the typical access constraints known from shovel-and-truck operations.

Using long stretched belt conveyors imposes an additional constraint. The conveyor on a particular bench can only be moved to the next position, if all the blocks in one pass are mined out. The Conveyor belt shifting constraint is schematically shown in Figure 3.3.

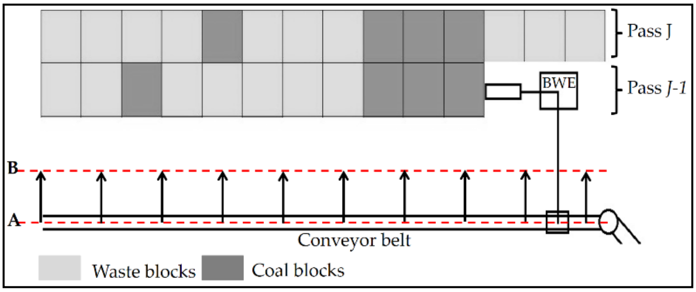

Figure 3.3. The conveyor belt shifting constraint: the conveyor belt can only be shifted from position A to B if all blocks in pass (*j-1*) are mined.

3.3.4. Decision Variables

The decision variables are a set of quantities that the decision maker controls. Decision variables are used as input variables in the discrete-event simulation model. They represent typical decisions on short-term planning and production control in a continuous surface mining operation. Some of the decision variables include:

- *extraction sequences*: sequence of extracting mining blocks for each excavator,
- *task schedules*: different alternatives for short-term mine plans (daily/ weekly/ monthly),
- *planned extraction rate* of excavators in the different time spans, or
- *stockpile management* in terms of the definition of stacking and reclaiming strategies or dividing the stockpile into sub-pockets.

The next section presents a set of steps that should be followed in a simulation study.

3.4. Steps of Simulation Modeling

Figure 3.4 presents a set of steps that will be followed in this study for developing a simulation model, designing experiments, and performing simulation analysis (Banks, 1998).

1. Problem formulation: The statement of the problem must provide the description of the purpose for building the model.
2. Setting of objectives and overall project plan: The defined objectives indicate the questions that are to be answered by the simulation study. Different scenarios that will be investigated should be included in the project plan.
3. Conceptual model: The system under study is abstracted by a conceptual model. In this dissertation, the conceptual model is a series of logical relationships concerning the components (e.g., excavators, spreaders, conveyor belts, etc.) and the structure (system topology) of the case study.
4. Data collection: This stage includes tasks of gathering as much data as possible about the system under study. The model parameters and input probabilities to be used in the model will be defined. Model building and data collection are shown as concurrent in Figure 3.4. The simulation modeler can construct the model while data collection is progressing.
5. Model translation: The constructed conceptual model in Step 3 is converted to an operational model. This step can be carried out using simulation software like Arena® (Rockwell Automation Technologies, Inc. 2012). The main tasks in this phase are the coding, debugging, and testing the operational model.
6. Verification of the model: This stage compares the output results of the operational model with those that would have been produced by a correct implementation of the conceptual model.

7. Validation of the model: This stage compares the outputs of the verified model with the outputs of the real system. It determines that the conceptual model is an accurate representation of system under study. If the system under study is an industrially relevant environment, in this step, TRL 6 will be achieved.
8. Documentation: All necessary information with the results of the analysis step should be documented.

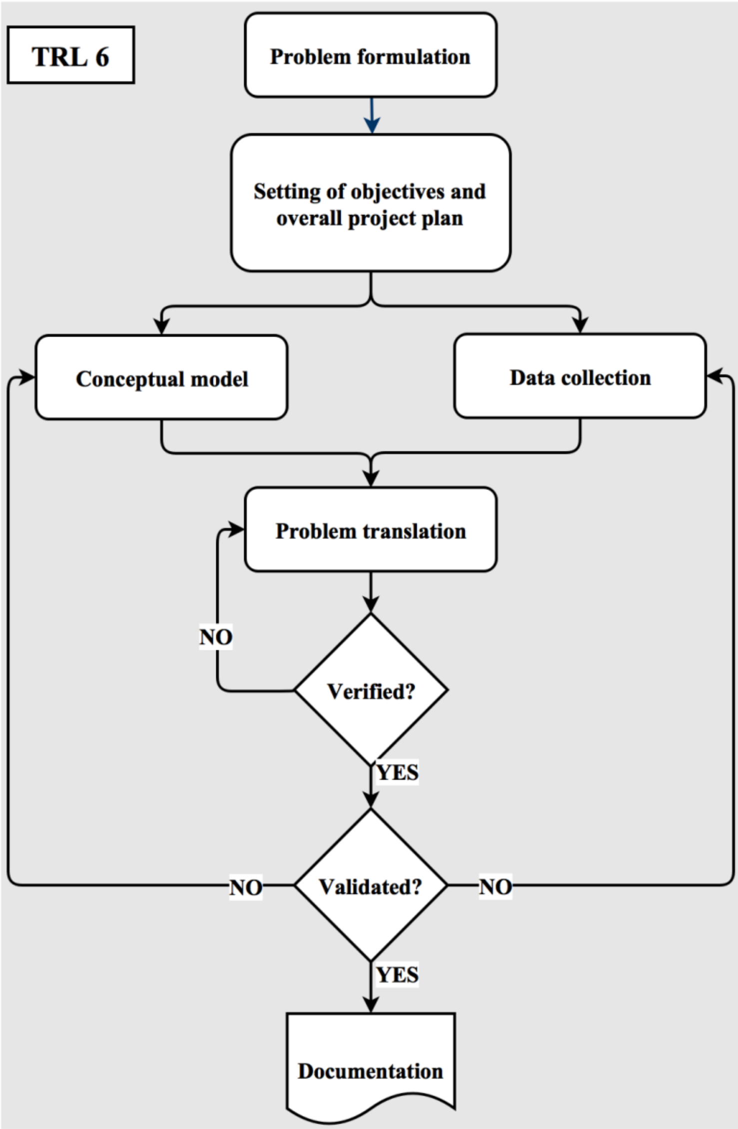

Figure 3.4. Steps in a simulation study (reproduced after (Banks, 1998)).

To understand the theory behind some steps, the following section elaborates on the verification and the validation steps.

3.5. Verification, Validation, and Evaluation Measures

One of the most difficult problems facing a simulation analyst is that of trying to determine whether a simulation model is an accurate representation of the real-world system. This section presents definitions, techniques, and steps of verification and validation (Kelton and Law, 2000).

- *Verification:* determination of whether the conceptual model has been correctly translated into a computer program.
- *Validation:* determination of whether a simulation model is an accurate representation of the system.

The chronological relationships of the validation and the verification are shown in Figure 3.5. The rectangles in part (a) of the figure represent states of the system under study, the solid horizontal arrows correspond to the actions necessary to move from one state to another, and the curved arrows show where the two major concepts are most prominently employed. The whole calibration process is mostly a trial-and-error procedure.

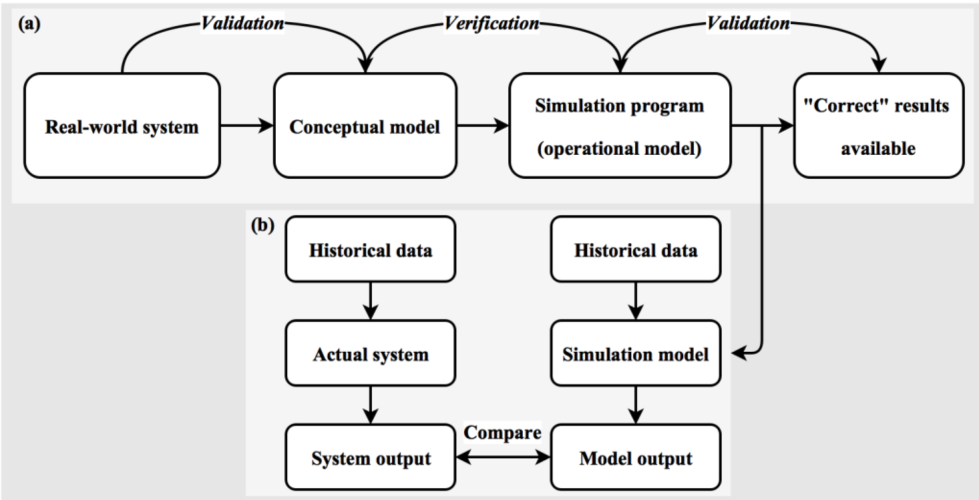

Figure 3.5. The applied approach for validation process (Reproduced after (Kelton and Law, 2000)).

The most definitive test of a simulation model's validity is to establish that its output result closely resembles the output result of the actual system. If the two sets of results compare "closely," then the model of the existing system is considered "valid". Part (b) in Figure 3.5 shows the applied approach in this study. The model is then modified so that it represents the proposed system. The greater the commonality between the conceptual model and real-world system is, the greater our confidence in the proposed model (Kelton and Law, 2000).

In this study, quantitative techniques are used to compare the output results of the simulation model with output results of the real system. Following evaluation measures are defined: bias, average deviation, and relative error.

- Bias: refers to the tendency of a measurement process to over- or under-estimate the value of a population parameter. The bias can be defined by Equation (3.5) as the sum of differences between all predicted and actual KPI values over all *n* predicted time intervals:

$$\mathrm{BIAS} = \sum_{n} (\mathrm{KPI}_{\mathrm{simulated}} - \mathrm{KPI}_{\mathrm{actual}}). \tag{3.5}$$

- Average deviation: is one of several indices of the prediction error. Within this study, it is defined as the mean absolute deviation between all predicted and actual KPI-values over all *n* predicted time intervals:

$$\mathrm{AVERAGE\ DEVIATION} = \frac{1}{n}\sum_{n} |\mathrm{KPI}_{\mathrm{simulated}} - \mathrm{KPI}_{\mathrm{actual}}|. \tag{3.6}$$

- Average relative error: the relative error is the absolute error (average deviation) divided by the magnitude of the actual value. Within this study, it is defined as:

$$\mathrm{AVERAGE\ RELATIVE\ ERROR} = \frac{1}{n}\sum_{n} \frac{|\mathrm{KPI}_{\mathrm{simulated}} - \mathrm{KPI}_{\mathrm{actual}}|}{\mathrm{KPI}_{\mathrm{actual}}}. \tag{3.7}$$

3.6. Simulation Modeling Software

The software selected to implement the simulation model is Rockwell ARENA® (Rockwell Automation Technologies, Inc. 2012), which allows closely reproducing the behavior of the complex real systems with complicated decision logic (Kelton and Law, 2000). The proposed simulation model of the continuous mining system is intended to reproduce the operation behavior in a real opencast coal mine. The extraction and conveying processes of the lignite and the waste are emulated in a combined discrete-continuous stochastic environment. This gives the possibility to recreate the deterministic and/or random occurrences of events such as operating stoppages, which are caused by unavailability of spreaders or conveyor belts, equipment failures, and preventive and corrective maintenance activities.

So far, a theoretical background to the stochastic simulation modeling process has been provided. The rest of the chapter will discuss the possibilities of coupling simulation and optimization, state of the art, and the proposed simulation-based optimization platform.

3.7. Coupling Simulation to Optimization

Simulation–optimization is a method that stems from the rapid and successful development of simulation and optimization techniques. The idea is to discover simultaneously the great detail provided by simulation and the capability of optimization techniques to find good or optimal solutions (Fu, 2002). The possibilities of coupling simulation and optimization are vast and the appropriate approach highly depends on the problem characteristics. Thus, before all, it is very important to have a good overview of the different approaches.

In the literature, different criteria are used to classify simulation-optimization approaches. Fu (1994) distinguished them based on properties of the optimization problem. The author separately discusses the discrete and the continuous parameter cases including techniques for optimization, however, the focus of the paper is on the latter. Some discriminated simulation–optimization methods by the applied techniques, e.g. gradient approaches, stochastic optimization, heuristics, statistical methods, etc., (Carson and Maria, 1997, Andradóttir, 1998, Fu, 2001, Ammeri et al., 2011). Banks et al. (2005) classified the approaches by their algorithms into four categories; approaches that (i) guarantee asymptotic convergence, (ii) guarantee optimality, (iii) guarantee a pre-specified probability of correct selection from a set of alternatives, or (iv) are based on heuristics. Fu (2002) considered the purpose of the stochastic simulation in the overall design as a key criterion. Based on this criterion the approaches are categorized into two main categories namely, “optimization for simulation” and “simulation for optimization”. Fu (2002) stated that their relation is not an equal partnership, but a subservient one. The former uses the optimization routine as an add-on to suggest candidate solutions to the simulator. The latter, in contrast, uses stochastic simulation to generate scenarios for math programming formulations from a set of possible realizations. However, the author has not discussed it further in the paper. Other classifications focus on the problem characteristics such as objective functions (e.g. single or multiple objectives), solution space (e.g. discrete or continuous), or shape of the response surface (e.g. global or local optimization) (Tekin and Sabuncuoglu, 2004, Barton and Meckesheimer, 2006, Ammeri et al., 2011). Recently, a comprehensive taxonomy for simulation–optimization methods was proposed by (Figueira and Almada-Lobo, 2014). The authors classified the simulation-optimization approaches based on four key dimensions: Simulation Purpose, Hierarchical Structure, Search Method, and Search Scheme. The first two are related to different ways in which simulation and optimization interact, whilst the other two concerned with the design of the search algorithm. The authors claim that, considering these four dimensions (and their full spectrum), they were able to cover the complete range of simulation–optimization methods and distinguish them in at least one dimension. Based on the Simulation Purpose, they distinguished three major streams as follows:

- Solution Evaluation (SE): Here, simulation is used to evaluate solutions and hence assess the response surface.
- Analytical Model Enhancement (AME): Simulation is used to enhance a given analytical model, either by refining its parameters or by extending it (e.g. for different scenarios).
- Solution Generation (SG): Simulation generates the solution based on the optimization output.

Based on the Hierarchical Structure, Figueira and Almada-Lobo (2014) categorized the simulation-optimization methods into four classes namely:

1. Optimization with simulation-based iterations – in all (or part) of the iterations of an optimization procedure, one or multiple complete simulation runs are performed, see Figure 3.6-a.
2. Alternative simulation-optimization – both components run alternatingly, see Figure 3.6-b.
3. Sequential simulation-optimization – both components run sequentially (either optimization following simulation or the opposite), see Figure 3.6-c.
4. Simulation with optimization-based iterations – in all (or part) of the iterations of a simulation process, a complete optimization procedure is performed, see Figure 3.6-d.

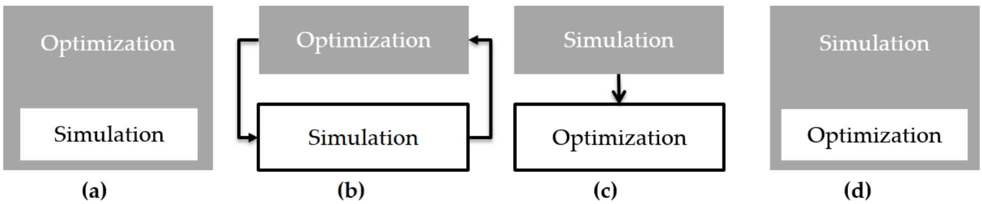

Figure 3.6. Four classes of simulation-optimization based on Hierarchical Structure, (Figueira and Almada-Lobo, 2014).

The categories defined for Search Method dimension are aligned with the major dichotomies in optimization problems such as exact vs heuristic; and continuous vs discrete (or combinatorial). Finally, in the Search Scheme the sequence of solutions and realizations are concerned, i.e. deterministic and stochastic problems are distinguished.

3.8. LITERATURE REVIEW ON THE APPLICATION OF SIMULATION-OPTIMIZATION

In the field of mining, little research to date has been carried out in the simulation-based optimization method. Mena et al. (2013) presented simulation and optimization modeling framework for allocating trucks by route based on their operating performance. In their optimization problem, equipment availability is a variable and the objective is to maximize the overall productivity of the fleet. Their computational cycle is such that the optimization model provides an initial set of decision variables. During the simulation run, when specific events (e.g. failure of a truck, etc.) occur, the optimization model is called to provide a new set of variables to the simulation model. Nageshwaraniyer et al. (2013a) proposed a two-level hierarchical simulation-based planning framework to maximize the revenue in each shift in one of the largest coal mine in the world. Trucks and trains system are used for the transportation of the material. Their framework reduces the decision space by separating the problem into sub-problems. These sub-problems are then solved such that the lower-level problems (the machinery scheduling problem) are constrained by the solution of the preceding higher-level problem (train-loading problem). In another study, Nageshwaraniyer et al. (2013b) investigated a robust simulation-based optimization approach for a truck-shovel system in surface coal mines. The objective is to maximize the expected value of revenue obtained from the delivered trains to customers. The Response Surface Method (RSM, (Jones, 2001)) is applied to define the variance expression of the objective function under different parameter settings of the simulation model. To obtain robust solutions, the authors added the variance expression as a constraint to the formulation of the optimization model.

Since there are few applications of the simulation-optimization approach in mining, it seems wise to focus on related fields, such as supply chain management, process system engineering, and scheduling of manufacturing environments to build upon their findings.

A supply chain management problem under demand uncertainty was presented by Jung et al. (2004) whereby safety stock levels were determined using a simulation-based optimization method in a rolling horizon manner. Their proposed approach consists of running alternatingly a deterministic planning model and a stochastic Monte-Carlo based simulation model in a loop structure. Their algorithm ends when the difference between the estimation and the target values of the customer satisfaction level is equal to very small number. Wan et al. (2005) present an extension to the proposed simulation-based optimization framework for analyzing supply chains. The extension consists of the iterative construction of a surrogate model based on simulation results. The model captures the relation between the decision variables and the performance of the supply chain. Instead of individual simulation runs, the decision variables can then be optimized using the surrogate model. The authors claim that the proposed framework can generally obtain better solutions with a smaller number of simulation runs. The framework can also readily handle chance constraints and does not present serious scale-up problems. Truong and Azadivar (2003) developed a hybrid optimization approach to address the supply chain configuration design problem. Their approach combines simulation, mixed integer programming and a genetic algorithm. The genetic algorithm provides a mechanism to optimize qualitative and policy variables. The mixed integer programming model reduces computing efforts by manipulating quantitative variables. Finally, simulation is used to evaluate performance of each supply chain configuration with non-linear, complex relationships, and under assumptions that are more realistic. Yoo et al. (2010) used discrete-event simulation to improve the efficiency of the supply chain optimization. This is done with the application of Nested partitioning (NP; global random search) and optimal computing budget allocation (OCBA; statistical selection). A general framework using a combination of simulation and optimization is presented by Almeder et al. (2009) to support operational decisions for supply chain networks. The authors claim that results are competitive and the method is faster compared to conventional methods. Othman and Mustaffa (2012) reviewed simulation and optimization methods applied in supply chain management.

Inventory optimization is one of the important topics in supply chain management. Köchel and Nieländer (2005) presented the application of the simulation optimization approach in multi-echelon inventory models. The search process in the optimization model is done by repeated processing of four stages using a genetic algorithm. The objective is to define optimal policies for the defined system. Lately, Chu et al. (2015) proposed a simulation-based optimization framework to optimize multi-echelon inventory systems under uncertainty. The framework is composed by agent-based modeling, simulation, the Monte-Carlo technique, a cutting plane algorithm, an experimental design technique, and statistical hypothesis tests. For the given inventory parameters, the agent-based model simulates the performance measures. The output of the model forms the objectives and the constraints of the optimization problem. The functions expectations in terms of sample averages are estimated using the Monte-Carlo method. After that, an iterative cutting plane algorithm is used to solve the optimization problem. When a solution passes the hypothetical tests, it can be considered as a local optimal solution. Subramaniam and Gosavi (2007) examined a problem related to replenishing inventories at retailers in distribution networks operated under the paradigm of Vendor-Managed Inventory (VMI). A simulation-optimization approach is developed to minimize the average cost per unit time of operating the entire system. A combination simultaneous perturbation (SP) and simulated annealing (SA) is integrated to a discrete-event simulation. Jalali and Van Nieuwenhuyse (2015) reviewed and classified the applied simulation-optimization methods for the inventory management problem.

The scheduling problem in manufacturing environments is another related field of interest. Hierarchical production planning creates a bridge between the long-term plans and short-term schedules. It has been applied in different problems such as a multi-plant production planning, planning of semiconductor wafer fabrication, flexible manufacturing system, a make-to-order environment, etc. (Venkateswaran and Son, 2005, Bang and Kim, 2010, Albey and Bilge, 2011, Gansterer et al., 2014). Lim et al. (2006) studied a production-distribution plan taking into account a multi-facility, multi-product, and multi-period problem. Their solution procedure for production-distribution planning consists of a mathematical solution procedure and a simulation solution procedure. First, the mathematical procedure is solved to decide the capacities of facilities and then outputs from this procedure are used to set the values of the inputs in the simulation procedure. The simulation procedure generates outputs, such as the production-distribution plans, as well as performance measures. If the outputs do not satisfy the required level, the replenishment policy in the factory and DC stages will be changed for the procedure. This approach continues iteratively until the desired optimal solutions are obtained. For a cooperative transportation problem, Sprenger and Mönch (2012) suggested a heuristic method using ant colony optimization combined with stochastic simulation. Discrete-event simulation is used to assess the method in a rolling horizon setting. Aqlan et al. (2014) applied simulation-optimization in the consolidation of production lines in a configure-to-order production environment. On one hand, the method uses MIP model to minimize transportation cost and waiting time. On the other hand, simulation provides recommendations and supports the decision-making. Lin and Chen (2015) studied the problem related to a real-world semiconductor back-end assembly facility. Simulation combined with a genetic algorithm is used to solve a hybrid flow-shop scheduling problem.

Subramanian et al. (2001) tackled a stochastic optimization problem in the context of R&D Pipeline management. The problem is an optimal resource-constrained project selection and task-scheduling problem in the face of significant uncertainty. They proposed a two-layer simulation-based optimization approach. The inner loop consists of a process optimizer, a process simulator, and a trigger event module. The simulator starts with an initial solution. When the simulation module encounters a need for control actions, it momentarily suspends itself and communicates the state of the system to the decision making module. The optimizer solves a combinatorial problem that is appropriately modified to account for the current system state. After that, the simulation is re-primed and it continues marching in time until its subsequent need for a control action. The outer loop (Subramanian et al., 2003) modifies the problem formulation, based on the knowledge obtained from the inner loop. It attempts to drive the controlled trajectories in the inner loop toward improving solutions with respect to probability distribution of the NPV in the system. "Sim-Opt" architecture (Figure 3.7), which is introduced by Subramanian et al. (2003), is applied in Chapter 6.

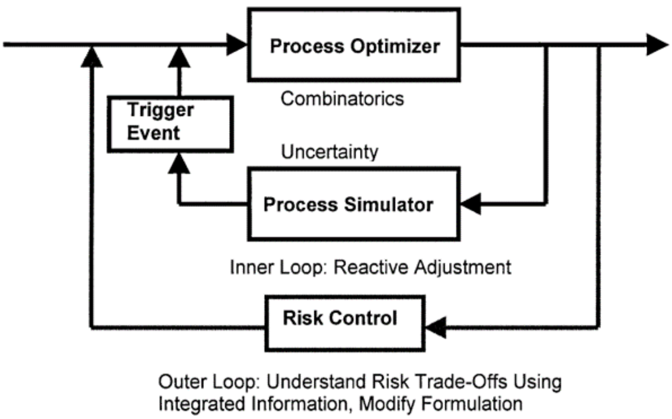

Figure 3.7. The "Sim-Opt" architecture (Subramanian et al., 2001).

3.9. PROPOSED SIMULATION-BASED OPTIMIZATION PLATFORM

To decide which methods are of particular interest, the before mentioned problem characteristics in Chapter 2 need to be considered. The first part of this dissertation develops a simulation model for continuous mining systems from extraction to coal stockpiling and waste dumping. As discussed earlier in this chapter, the simulation model captures different sources of uncertainty (e.g. equipment failures, geological uncertainty) and their interdependencies. Additionally, the simulator integrates decision variables representing decisions to be made in short-term production scheduling and therefore can be utilized during the optimization process to suggest optimal dispatch decisions to the user. Choices that need to be made might be for instance the equipment's schedule (connection of BWEs to spreaders), the equipment's digging/dumping locations, the equipment's capacities, or the schedule of auxiliary actions such as belt shifting. Thus, the optimization and the simulation modules need to be alternatingly connected. Moreover, the simulation module always requires inputs from the optimization module. Taken together, the alternating simulation-optimization class (Figure 3.6-b) seems to be more suitable for this problem. Furthermore, based on the size and the characteristics of the problem, the exact search method with stochastic search scheme is recommended.

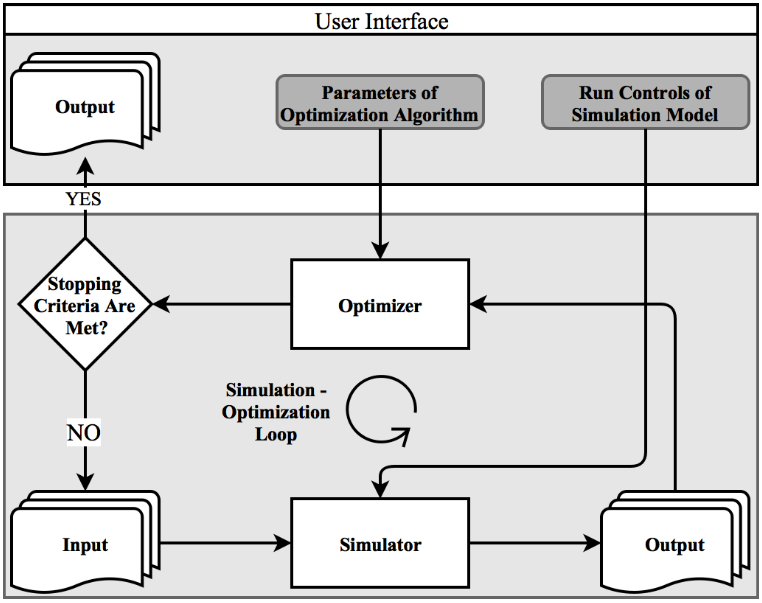

Figure 3.8. The suggested simulation-based optimization platform (reproduced after (Halim and Seck, 2011)).

Figure 3.8 depicts the concept of the suggested platform in this dissertation for the simulation-optimization process. Hereafter, this platform is called "simulation-based optimization" approach (Halim and Seck, 2011). In this approach, the simulation model functions as the evaluator of the objective functions that are to be optimized by the optimization module. The user interface provides the user the flexibility to set the parameters of the optimization algorithm and the run control of the simulation model (the details are discussed in Chapter 6). Once the entire necessary configuration has been set, the optimizer will start with initial solutions for which evaluations using the simulation are performed. In other words, the optimizer calls the simulator and provides a new set of decision variables in each iteration step. The simulator simulates the mining operation for the given set of decision variables and based on the results, the system's KPIs can be estimated. The results of the evaluations are then used by the optimization algorithm to generate new solutions that are expected to be better than the previous solutions. This loop continues until the stopping criteria of the optimization algorithm are met.

4

SYNTHETIC EXPERIMENT: 2D CASE STUDY

The contents of this chapter have been adapted from:

Shishvan, M. S., & Benndorf, J. (2014). Performance optimization of complex continuous mining system using stochastic simulation. Paper presented at the Engineering Optimization IV, LISBON, PORTUGAL.

Shishvan, M. S., & Benndorf, J. (2016). The effect of geological uncertainty on achieving short-term targets: A quantitative approach using stochastic process simulation. Journal of the Southern African Institute of Mining and Metallurgy, 116(3), 259-264.

The algorithmic approach to simulate the process of continuous mining systems was developed in the previous chapter. This chapter conducts an extensive experiment in a synthetic 2D dataset to quantify the effect of geological uncertainty on production performance in terms of coal tonnage produced per coal type, probability of meeting quality specifications of coal produced, and system efficiency in terms of utilization of major equipment.

4.1. METHODOLOGY

To illustrate the effects of geological uncertainty on the performance of a complex continuous mining system using the previously described approach, a case study is presented in a completely known and fully controllable environment, a synthetic data set. This allows benchmarking against the 'ground-truth'. Without loss of generality, a selection of two 2D representations of the coal quantity and coal quality is chosen, each representing a bench. Each digging block is a 2D rectangle limited by the current and upper working bench and contains an amount of waste, coal and its qualities. To further demonstrate the benefit of using geostatistical simulated deposit models, two models were built based on sample data derived from the exhaustive data set, one estimated model using Kriging and one consisting of 20 conditionally simulated realizations using Sequential Gaussian Simulation. The latter one will allow running 20 replications, as defined in section 3.3.

The aim is to quantify the effects of geological uncertainty, downtimes, and their impacts on the ability to deliver contractually defined coal quantities and qualities. The solution strategy is to combine two simulation concepts: geostatistical simulation for capturing geological uncertainty and stochastic process simulation to predict the large continuous mining system's performance and reliability.

4.1.1. EXPERIMENTAL SETUP

In this example, the mining operation uses six BWEs, which are positioned on six benches. The extracted materials are transported by conveyor belts to the mass distribution center. Here, they are distributed to their predefined destinations. Finally, waste materials are conveyed to the dump site and coal to the stockpile yard. At the stockpile yard, a simplified Chevron blending strategy is used for blending of coal. Afterward, trains deliver coal to customers with contractually defined coal quantities and qualities. The following details of the mining operation are assumed:

- BWE 1 performs pre-stripping and solely extracts waste (sand, gravel, clay) and is connected to spreader 2,
- BWE 2 and 3 extract partly coal and partly waste, which can be sent the both spreaders, and

- BWE 4, 5, 6 extract coal and waste and have access to spreader 1 and the coal bunker.

The reserve block model contains 93,600 mining blocks. The volume of each mining block is about 15,400 m3. The block model is equally divided into six benches; each one is assigned as a resource to one excavator (Figure 4.1). As mentioned earlier, blocks contain quantity and quality parameters as attributes. Coal (green) and waste (dark blue) blocks can easily be seen in Figure 4.1. For demonstration reasons, the ash value is chosen for this study, acknowledging that the study can be performed for any coal quality parameter.

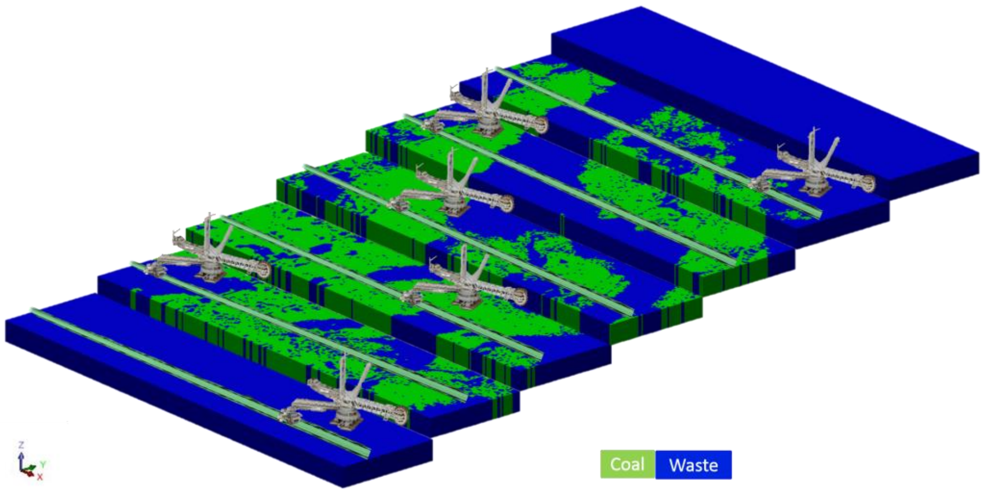

Figure 4.1. Reserve block model and the assigned areas for the excavators.

Based on the ash value of estimated model, coal blocks are classified in two categories, namely coal type 1 and coal type 2. The former is high quality coal with an ash content of less than 9% and the latter is low quality coal, with an ash content between 9% and 12.5% (see Table 4.1).

Table 4.1. Technical parameters

Material types		Targets		Penalties	
Type	Density	Max	Min	Upper	Lower
Coal Quantity		650,000 (T)	700,000(T)	1	15
Coal Type 1	1	Ash content < 9%		1	
Coal Type 2		9% < Ash content < 12.5%		1	

4.1.2. Simulation Model Construction

In this case, the following steps are involved in the simulation modeling of a synthetic mine.

- The first step is to define appropriate entities. Entities are defined as the block portions to be extracted in each period.
- The second step is to assign block attributes. As an entity arrives into the system, its attributes consisting of block coordinates (x, y and z), block tonnage, block type, quality parameters, and destination are assigned. These attributes are read from the geological block model.
- Subsequently, the entity is placed in a queue to seize on the excavator as a resource module in the simulation model.
- Each entity has a delay based on operating time and will then be released.
- At the final step, variables such as total waste tonnage, ore tonnage, and corresponding quality parameters such as ash content are calculated.

A capacity constraint is implemented to prevent overflow of loose material on the conveyor belt that is connected to the coal-bunker. Based on the maximum capacity of the conveyor belts, a constraint of 6000 $m^3/hour$ is considered for coal. While the production rate exceeds these limits, the model starts to identify the excavators that are producing coal. It is decided that the excavator that corresponds to the minimum production rate is set to standby.

Decision variables of this case consist of:

- Task schedule: A working schedule for a time horizon of 15 days is given in Table 4.2. This mine operates 24 hours per day in three working shifts. For instance, the number 110 in the table shows that the associated equipment is available in the first and the second shifts and is inactive in the third shift.

Table 4.2. Working schedule of the equipment as a decision variable.

Type	Days														
of equipment	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Excavator 1	111	001	111	111	111	111	111	111	111	111	100	111	111	111	111
Excavator 2	111	111	111	001	111	111	111	111	100	111	111	111	111	111	111
Excavator 3	111	011	111	001	111	111	111	111	100	111	111	111	111	111	111
Excavator 4	111	111	111	111	111	111	111	111	111	111	111	111	111	001	111
Excavator 5	111	111	001	111	111	111	111	111	111	111	100	111	111	111	111
Excavator 6	111	110	110	111	111	111	111	111	111	111	111	011	111	111	111
Spreader 1	111	111	111	001	111	111	111	111	001	111	111	111	111	111	111
Spreader 2	111	001	111	111	111	111	111	111	111	111	001	111	111	111	111
Conveyor belts	111	111	111	111	111	111	111	111	111	111	111	111	111	111	111

- Extraction sequence: A constant sequence, which is from one side of the bench to the other side is considered. (There are no extra movements for excavators during the excavation.)
- Extraction rate of excavators: Table 4.3 provides the excavation rates of the BWEs.
- Stockpile management: It is assumed that if the stockpile for a specific coal type is full, excavator(s) that produce(s) that kind of coal should be idled until opening a space.

Table 4.3 gives some general information and technical parameters that are used for the simulation model building.

Table 4.3. General information of equipment

Type	Theoretical Capacity ($m^3/hour$)	Scheduled Time $T_{scheduled}$ (h)	Hourly Standby Cost (€)
Excavator 1	4900	328	3000
Excavator 2	4900	328	3000
Excavator 3	3770	320	2500
Excavator 4	1400	344	2000
Excavator 5	3770	328	2500
Excavator 6	740	336	1500
Spreader 1	10,000	328	-
Spreader 2	10,000	328	-
Conveyor belts	6000	360	-

4.1.3. Integrated Simulation Approach

In this dissertation, combining two simulation concepts as a solution strategy for quantifying the effects of geological uncertainty on achieving short-term targets is suggested. Figure 4.2 shows the proposed integrated simulation approach. In this approach, realizations of the reserve block model based on conditional simulation and an interpolated model using Kriging are considered as inputs for the mine process simulator. The output of the simulator is the set of values for the measured KPIs. At this stage, penalties are applied if deviating from production targets were seen. Finally, the KPIs are summarized in an evaluation function (as discussed in Section 3.3.1). Finally, if multiple simulation replications are evaluated, a probability distribution is constructed, see Figure 4.2. The next section will elaborate on how to model or predict random behavior of the equipment in a simulation model.

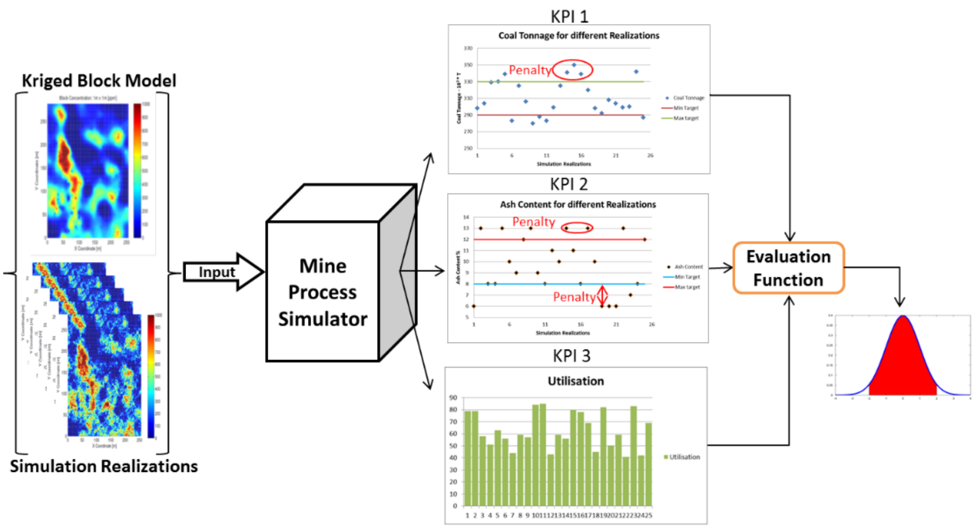

Figure 4.2. The proposed integrated simulation approach.

4.1.4. Statistical Analysis and Failure Modeling

To carry out a simulation using random inputs such as breakdowns of equipment, it is necessary to specify their probability distributions. It must be emphasized that improper probability distributions can destroy the value of the results that flow from a simulation study (Kelton and Law, 2000). The first task is to determine if the collected data does indeed belong to a homogenous stochastic process or not. This requires two tests: first to determine if the stochastic process is identically distributed and the second to determine if the constituent random variables are independent or not. The final task is to fit a theoretical distribution to the collected data (Birta and Arbez, 2013).

In this case, a database consists of six months of the operational data (in total over hundred thousand records) is used for modeling the behavior of the equipment. The long-term production data indeed show stationary and independent behavior in which the average values within the collected data remain invariant over the time.

Fitting a theoretical distribution that matches time series data obtained from a homogenous stochastic process is usually a trial-and-error procedure and begins with a histogram developed from the collected data. In this case, two types of unscheduled breakdowns of equipment, which are caused by mechanical and electrical failures, are considered. Depending on the failure mode, Gamma, Weibull, Uniform, etc. distributions were found to fit best. Table 4.4 presents the all used probability distributions of the equipment in the simulation modeling process. These models play the role of input failure data to the simulation model.

Table 4.4. Analyzed failure data.

Type of equipment	Time Between Failure (TBF)#	Time To Repair (TTR)#
M Failure EXC1*	905 * BETA(0.305, 0.444)	LOGN(6.09, 19.8)
M Failure EXC2	WEIB(62.5, 0.652)	LOGN(1.99, 3.64)
M Failure EXC3	TRIA(14, 94.4, 550)	LOGN(1.72, 2.08)
M Failure EXC5	127 + WEIB(118, 0.377)	0.11 + 1.39 * BETA(0.997, 1.08)
M Failure EXC6	235 + 65 * BETA(0.268, 0.302)	1.03 + 0.35 * BETA(1.13, 0.974)
E Failure EXC1**	10 + EXPO(213)	0.18 + 0.97 * BETA(0.496, 0.788)
E Failure EXC2	GAMM(191, 0.454)	WEIB(2.23, 0.462)
E Failure EXC3	290 * BETA(0.453, 1.14)	WEIB(1.4, 0.485)
E Failure EXC5	GAMM(129, 0.615)	LOGN(0.734, 0.544)
E Failure EXC6	UNIF(198, 979)	0.15 + 0.37 * BETA(0.614, 0.654)
M Failure Spreader 1	UNIF(364, 852)	0.09 + 1.23 * BETA(0.845, 1.02)
M Failure Spreader 2	EXPO(129)	LOGN(2.94, 7.19)
E Failure Spreader 1	12 + EXPO(118)	LOGN(7.19, 19.2)
E Failure Spreader 2	91 + 706 * BETA(0.221, 0.29)	75 * BETA(0.274, 0.457)

*M: Mechanical **E: Electrical #The unit is hours

4.1.5. Coal-Blending Strategy

Decisions are included in stockpile management, such as (i) sequence of stacking, (ii) sequence of reclaiming and (iii) size of the stockpile. In order to reduce both short- and long- term fluctuations of coal quality characteristics, various blending techniques have been proposed. In this study, a Chevron-Type stockpile is used; however, it is modified according to the simulation modeling circumstances. As is shown in Figure 4.3, the final shape of the stockpile, which is a triangular prism, is converted to a block model with equal cell dimensions based on the stacking time. The size and the attributes of each cell such as tonnage, ash, and CV content are calculated based on the stockpile geometry. From the four stockpiles, two are designated coal type 1 and the rest coal type 2. For the purpose of blending, the stacker operates in a zigzag pattern and the reclaimer performs the same pattern but perpendicular to the stacking operation as can be seen in Figure 4.3.

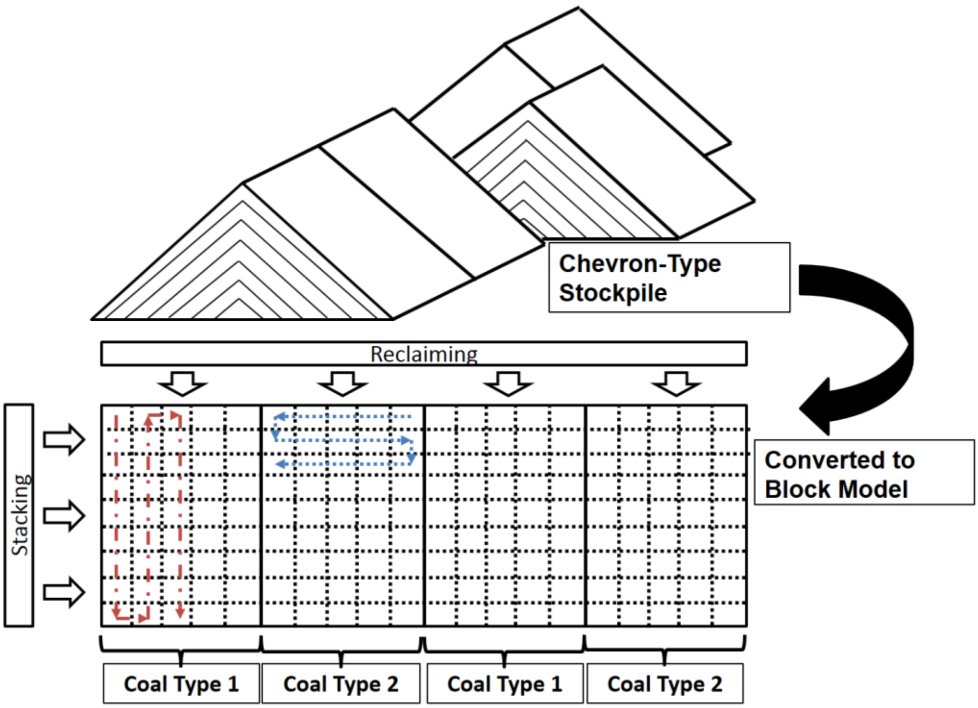

Figure 4.3. A Chevron-type blending strategy, (adapted from Benndorf (2013b)).

4.1.6. Simulation Modeling Experiments

Appropriate use of a simulation model requires decisions concerning two key parameters: number of replications and run-length. The limiting factors will be computing time and expense. The aim is to produce multiple samples in order to obtain a better estimate of mean performance (Kelton and Law, 2000). The question therefore arises: "how many replications are needed?" Assuming that performing *N* replications achieves a satisfactory estimate of mean performance as required by the user, performing more than *N* replications might be an unnecessary use of computer time at a considerable expense. However, performing fewer than *N* replications could lead to inaccurate results and thus to incorrect decisions being made. In this study, a simple Graphical Method (Robinson, 2004) is used for selecting the minimum appropriate number of replications. To achieve this, a list of performed experiments is provided in Table 4.5. As an example, the results for a run length of 15 days with different numbers of replications are displayed in Figure 4.4. As can be seen, the scaled cumulative mean of the chosen output variables (ash, CV, and coal tonnage) are plotted against the number of replications. Based on the graphical method, the point on the graph where the cumulative mean line becomes "flat" is visually selected as the appropriate number of replications. In this case, 20 replications seem to be the suitable number. It should be noted that the run length, in this case, directly depends on the length of the task schedule. However, for the purpose of comparison, different run lengths are examined.

Table 4.5. Lists of performed experiments.

Run Length	Source of Uncertainty			
	Geological Uncertainty & Downtimes			
	Number of Replications			
7 days	10	20	30	50
15 days	10	20	30	50
30 days	10	20	30	50
60 days	10	20	30	50

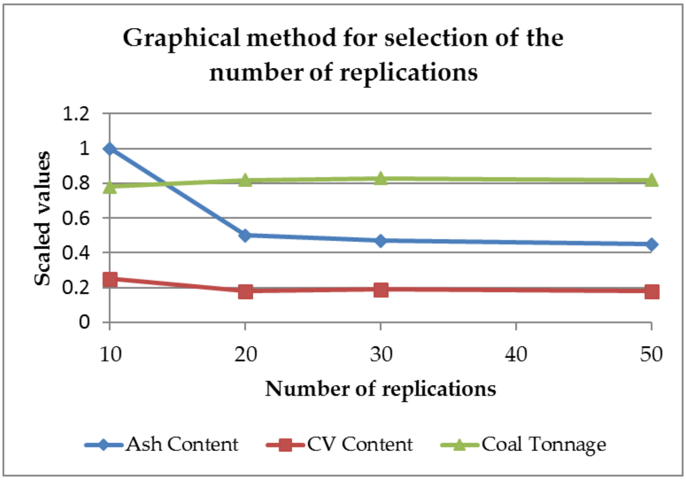

Figure 4.4. A simple graphical method for the selection of the number of replications.

4.2. Results

This section provides some representative results from the performed experiments. The results that are presented in this section consider these points:

- The synthetic dataset represents a fully known and controllable environment, thus the assessment of geological uncertainty is based on 22 different reserve block models: real value, estimated and 20 realizations.

- The measured KPIs are coal quality, coal quantity, and utilization (defined in Section 3.3.2).
- Results for a run length of 15 days and 20 replications are presented.
- Penalties are calculated based on parameters specified in Table 4.1.

4.2.1. COAL QUALITY - KPI

Figure 4.5 presents the average ash content of extracted coal for the real value model (light grey), the estimated model (Black), the realizations (dark grey) and the average of simulation (red line). The ash contents of all realizations substantially exceed the value predicted by the estimated deposit model. On the other hand, the real model shows a very similar value to the average value of the 20 realizations (Red line). Taken together, relying on the estimated model would result in a biased and too optimistic ash content.

The penalties that are applied due to not meeting the coal quality target are shown in Figure 4.6. These penalties are calculated based on Equation (3.2). Costs of deviation from the targets (the penalties) in this study are unity for each percentage of the deviation per tonne of coal (1 €/(%.tonne)). Hence, these penalties can be interpreted as costs (€) that must be deducted from the total profit of the mine. Except for the estimated model, all realizations and real model are penalized. This illustrates that the chance of deviating from the target, especially in this case, is almost 100%.

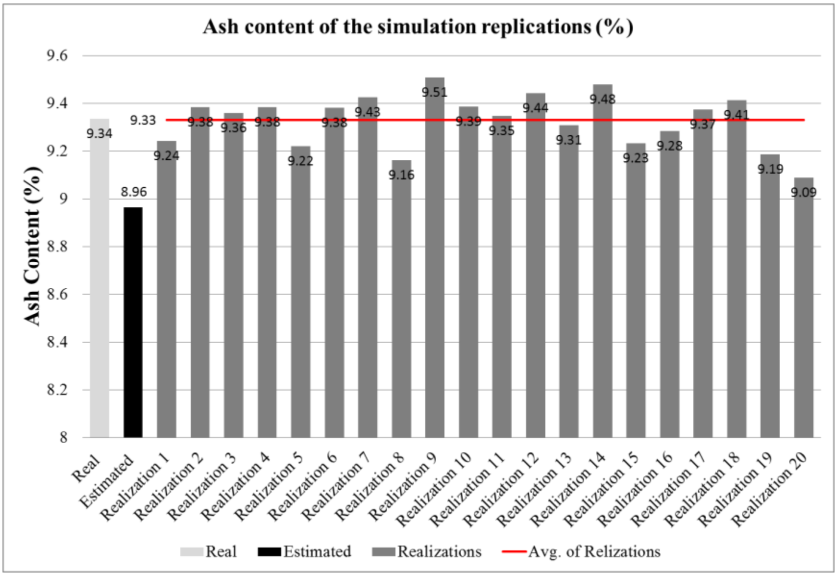

Figure 4.5. Illustrative results of the ash contents of different scenarios.

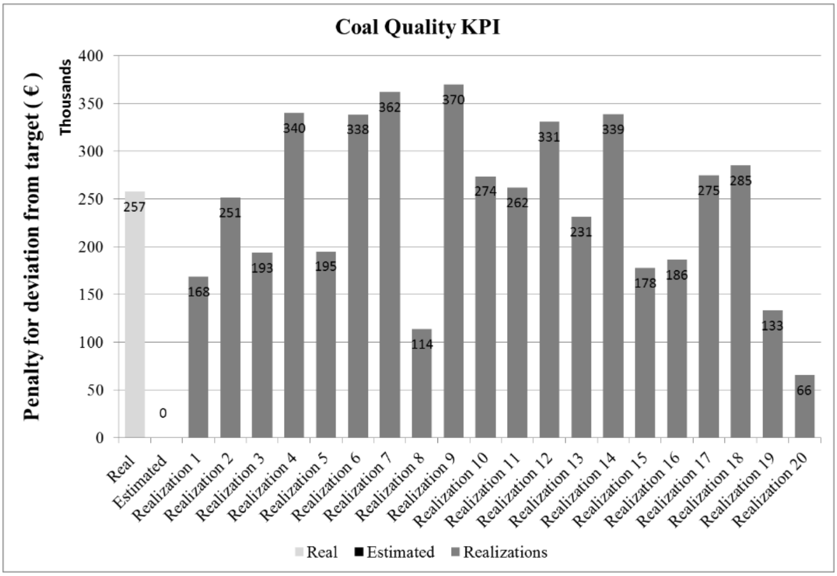

Figure 4.6. Penalties that are calculated due to not meeting the quality targets.

4.2.2. COAL QUANTITY - KPI

The total extracted coal tonnages for the different scenarios are presented in Figure 4.7. The system simulation based on the estimated model shows significantly less coal (10%) than the average value of the 20 realizations (Red line). The average value is again similar to the real value. Clearly, the estimated model underestimates coal production for the defined schedule. This is mainly due to ignoring in-situ variability and geological uncertainty. The capability of conditional simulation to quantify geological uncertainty adds an additional dimension to the prediction of system performance.

Figure 4.7, also, indicates that for example realization 3 will lead to an underproduction of 110kt of coal. To account for this uncertainty the stockpile inventory should be at least 110kt before the start of the week to accommodate potential deviations from targets and secure a safe supply to customers. Note that the application of average-type estimated models does not always lead to underestimation. Depending on local geological conditions, these techniques may also lead to an overestimation.

Figure 4.8 shows penalties that are applied due to not meeting the coal quantity targets. In this KPI, the costs of deviation from the targets (the penalties) are unity for one tonne of coal (1 €/tonne) for the overproduction and 15 units for a tonne of coal for the underproduction. Similar to the coal quality KPI, these penalties are calculated based on Equation (3.3). They can be interpreted as extra costs that decrease the total profit.

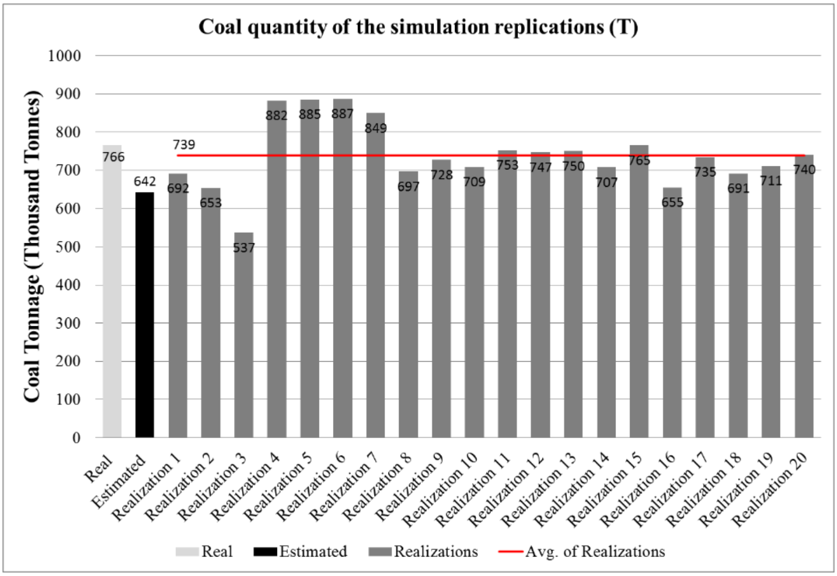

Figure 4.7. Illustrative results of the coal quantity KPI for different scenarios.

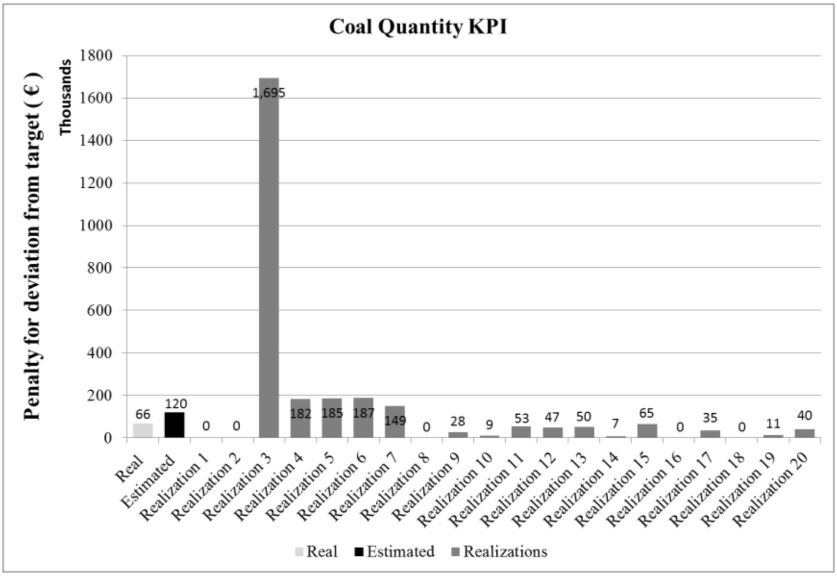

Figure 4.8. Penalties that are calculated due to not meeting the quantity target.

Geological uncertainty does not only affect the amount of coal produced, but also waste management and downtime due to dispatching. Waste management plays a key role in the optimal dump control. To analyze the uncertainty in predicting the amount of waste for each spreader, box plots are used to show the variations in waste tonnage dumped by the spreaders (Figure 4.9.

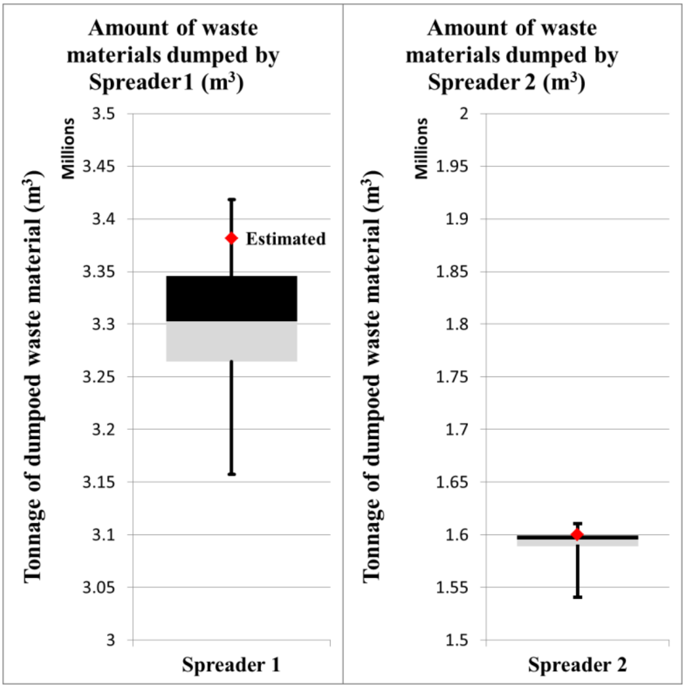

Figure 4.9. Waste extraction tonnages of excavators.

4.2.3. UTILIZATION - KPI

The boxplots of active digging times of BWEs during the time horizon are given in Figure 4.10. As can be seen, the ranges of active hours for BWEs are rather disperse and in almost all the box plots, the four sections (quartiles) of the box plot are uneven in size. The differences between the active hours and the scheduled hours are the results of the dispatch delays and unscheduled breakdowns. For each excavator the effect of existing variability and uncertainty can be assessed and used for improved decision making. Figure 4.11 demonstrates the average utilization of the system for different reserve block models. Evidently, geological uncertainty, variability, and unscheduled breakdowns have a significant impact on the measured KPIs.

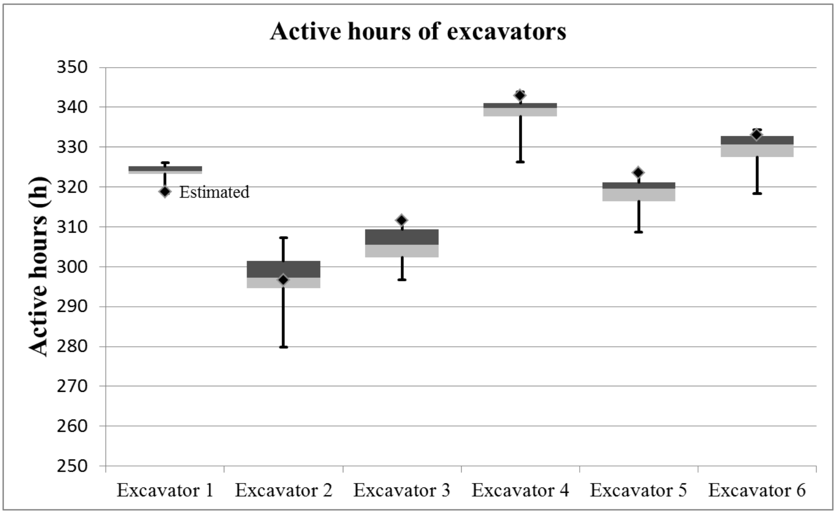

Figure 4.10. Boxplots of active hours of BWEs.

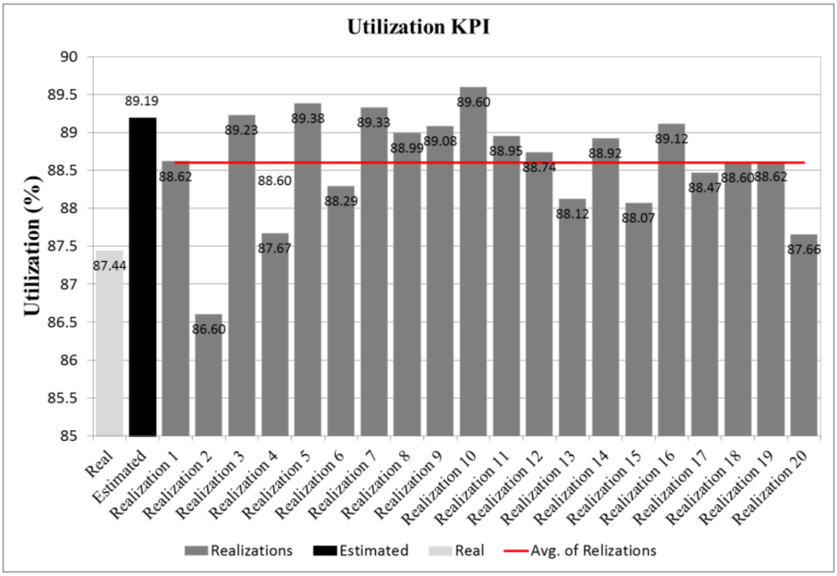

Figure 4.11. Values of the utilization KPI for different simulation replications (scenarios).

Figure 4.12 shows penalties due to not meeting the utilization KPI. Values are calculated by multiplying the difference between the scheduled working hours and the actual working hours to the hourly standby costs (see Table 4.3). Like the other two KPIs, these values are costs that reduce the overall profit of the mine.

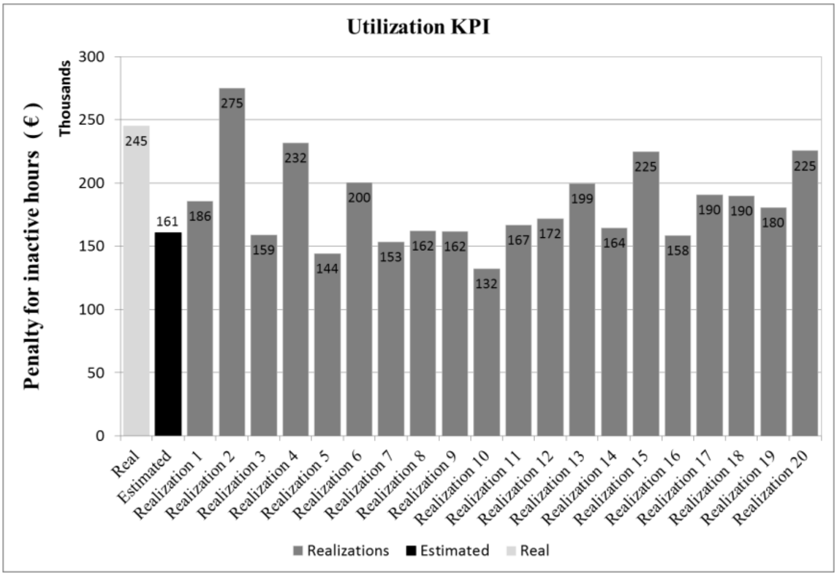

Figure 4.12. Penalties that are calculated due to not meeting the utilization KPI.

4.2.4. Calculation of Evaluation Function

The final step in the integrated simulation approach is the summation of all measured KPIs in an evaluation function. Penalties and quantified values of the evaluation function for different reserve block models (when coefficient C_{nt} in Equation (3.1) is equal to one (base case)) are given in Table 4.6.

Histograms for the base case with statistical measures like mean, standard deviation, 10% quantile, 50% quantile, and 90% quantile are presented in Figure 4.13. The blue bar shows the frequency of realizations in a specific bin, the dashed-line is the value of the evaluation function of the estimated model, and the solid line is the value of the real model. It can be seen that the value for the estimated model is lower than the 10% quantile. This illustrates the fact that the probability of its occurrence is very low. On the other hand, the mean value of the calculated evaluation functions of realizations is close to the real value model. It can be concluded that, based on the histogram, the probability of occurrence of the average of realizations is relatively high.

4

Table 4.6. Penalties and quantified values of the evaluation function for different reserve block models.

	Quality KPI (10^3 €)	Quantity KPI (10^3 €)	Utilization KPI (10^3 €)	Evaluation Function (10^3 €)
Real	257.35	66.18	245.13	568.66
Estimated	0.00	120.31	160.64	280.94
Realization 1	168.45	0.00	185.67	354.11
Realization 2	251.39	0.00	274.85	526.24
Realization 3	193.47	1694.62	159.00	2047.09
Realization 4	339.69	182.46	231.55	753.69
Realization 5	195.06	185.44	144.07	524.57
Realization 6	338.34	186.95	200.42	725.71
Realization 7	361.93	149.20	153.17	664.31
Realization 8	113.74	0.00	162.07	275.81
Realization 9	369.82	27.50	161.68	559.01
Realization 10	273.76	8.72	132.15	414.62
Realization 11	261.81	52.55	166.53	480.89
Realization 12	330.60	46.99	171.61	549.20
Realization 13	231.12	50.13	199.28	480.53
Realization 14	338.88	7.31	164.41	510.59
Realization 15	177.56	65.33	224.96	467.85
Realization 16	186.10	0.00	158.19	344.29
Realization 17	274.59	34.65	190.49	499.74
Realization 18	284.93	0.00	189.58	474.50
Realization 19	133.43	11.32	180.39	325.13
Realization 20	65.60	40.01	225.42	331.04

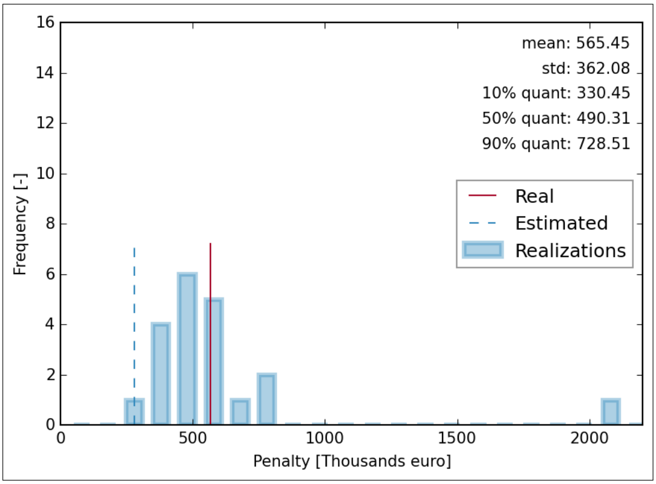

Figure 4.13. Histogram of values for the evaluation functions ($C_{nt} = 1$).

The value for coefficient C_{nt} in the evaluation function is equal to either zero or one. Zero means that the KPI has no effect in the management strategy, which is taken in the mine, and one means the opposite. To investigate different management objectives, six other different scenarios are considered. The list of scenarios based on different values for coefficient C_{nt} can be found in Table 4.7. Evaluation functions for these scenarios are calculated; they are presented as histograms in Figure 4.14.

Table 4.7. Different management scenarios for the evaluation of simulation model's outputs.

KPIs	Scenarios					
	1	2	3	4	5	6
Quality KPI – C_1	0	1	1	1	0	0
Quantity KPI – C_2	1	0	1	0	1	0
Utilization KPI – C_3	1	1	0	0	0	1

As can be seen in Table 4.6, the estimated model has not gotten any penalty for the quality KPI. When this KPI is not important in the management strategy, i.e. C_1 is equal to zero (Scenarios 1, 5, and 6 in Table 4.7), the penalty value of the estimated model comes closer to the real value model and the mean value of the realizations, see Figure 4.14. Thus, the probability of occurrence of the average of realizations is relatively high. The effects of geological uncertainty are more visible enhanced in scenario 2 and 4 where the probability of its occurrence based on the estimated method is almost equal to zero. Hence, it can be concluded that depending only on the estimated model will result in a biased and an optimistic prediction of the ash content. Scenario 3 shows a similar behavior as the base case (see Figure 4.13), however, penalties due to not meeting targets are decreased.

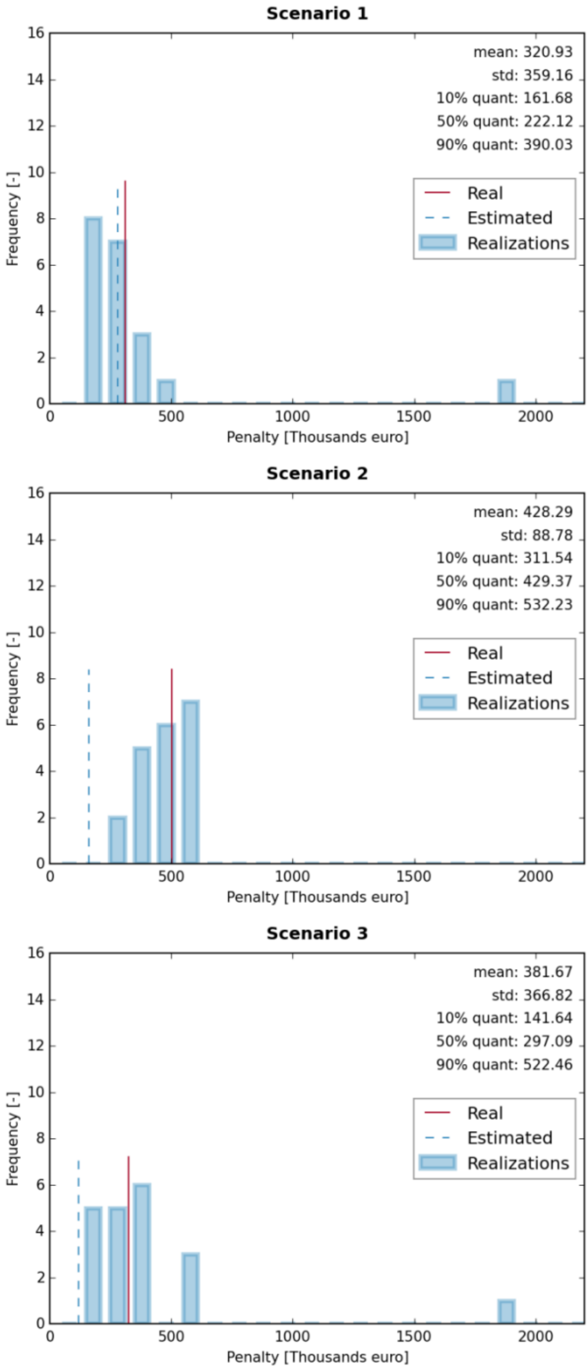

Figure 4.14. Histograms of different scenarios.

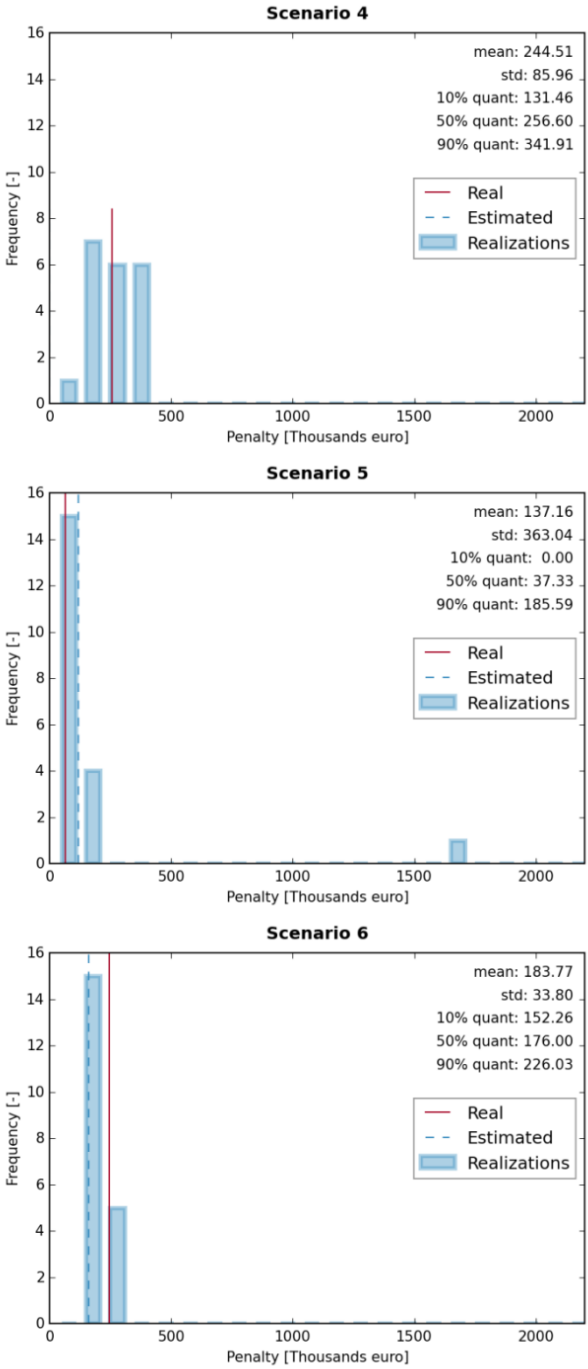

Figure 4.14. Continued (2) Histograms of different scenarios.

4.3. Discussion

In opencast lignite mines, decisions about the destination of the extracted coal have to be made prior to excavation, when the reality is not known yet. Therefore, classification of coal type and stacking in the different locations are based on the estimated model. In fact, the true quality of delivered coal is defined based on samples taken from the train cars. A laboratory analyzes the samples and their reported results represent the "reality". The results, normally, take at least three days to be obtained.

As noted earlier, coal type 1 is high quality coal (ash content is less than 9%) and coal type 2 is lower quality coal (ash content is between 9-12.5%). Figure 4.15 and Figure 4.16 show the ash content of delivered trains to customers. The results reveal that the estimated model (dotted-black line) and the reality (dark grey line) are not well correlated. The reality clearly shows deviations from the target. On the other hand, the estimated model does not forecast any deviations. This illustrates the limits of predictions based on the estimated (interpolated) model. In the conditional simulation models, there are 20 realizations (light grey cloud) and the average of the realizations (dashed-red line). These models can predict the probabilities of deviations. For example, for each train there is a distribution of the ash contents, which is a stochastic prediction. These stochastic predictions are mapped by the shadow range (realizations cloud); it illustrates the range of uncertainty (deviations).

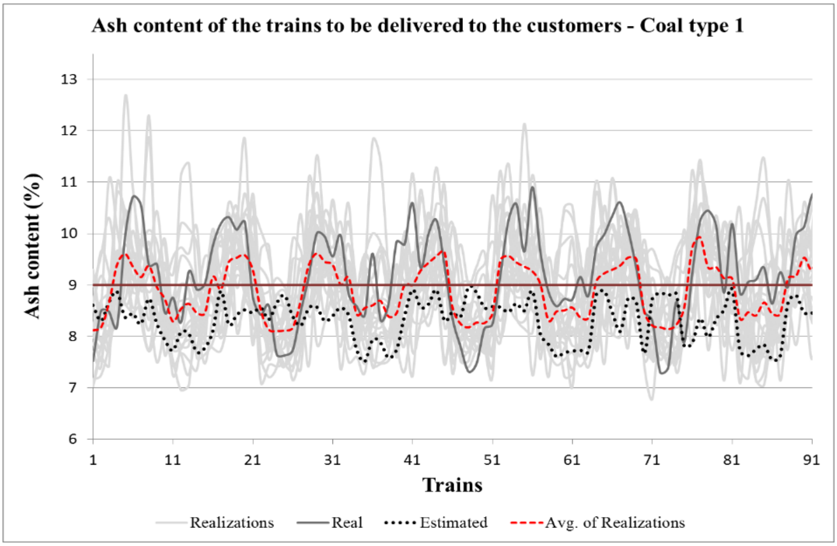

Figure 4.15. Ash contents of delivered trains of coal type 1.

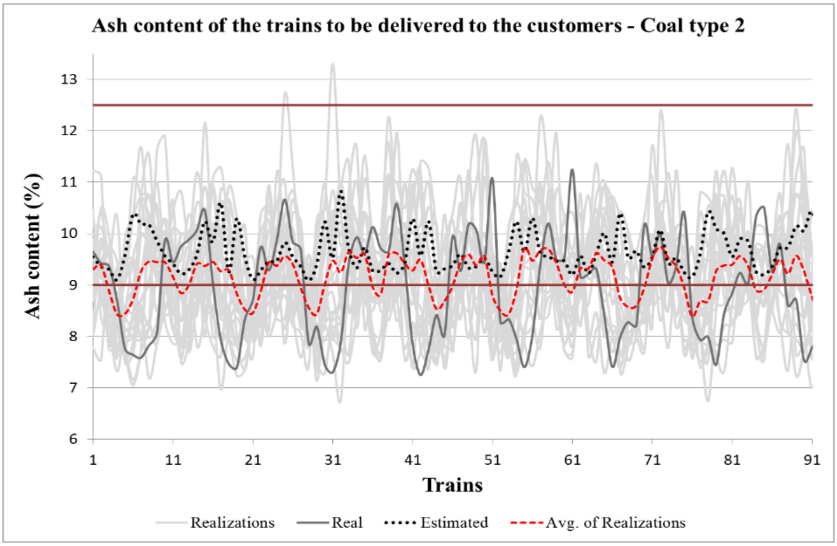

Figure 4.16. Ash contents of delivered trains of coal type 2.

The most striking result emerging from the above graphs is that the reality and the average of the realizations are surrounded by the realizations cloud. The average of the realizations reasonably follows the trend of the reality. However, some deviations are seen but these deviations are also in the expected range of uncertainty (realization cloud).

Furthermore, the histogram of probabilities is used for illustration of the effect of the geological uncertainty. Probabilities of the ash content of the delivered trains to be more than 9% are calculated. Then frequencies of the trains versus probability bins are shown as a histogram in Figure 4.17. The stochastic prediction proposes that the ash content of 42 trains out of 90 exceeds the threshold. However, in reality 49 trains show a deviation from the target. More than 50% of the trains contain low quality coal. This can cause a big financial loss for the mine if the profit is penalized by customers. On the other hand, for coal type 2 probabilities are calculated when the ash content of the delivered trains is less than 9%. Figure 4.18 shows the obtained histogram. Based on the probabilities, 43 trains out of 90 are expected to go beyond the threshold and the reality illustrates that this value is 40 trains. It can be concluded that high quality coal has been loaded into the trains that are sent to customers of the less quality coal. This will incur an opportunity cost.

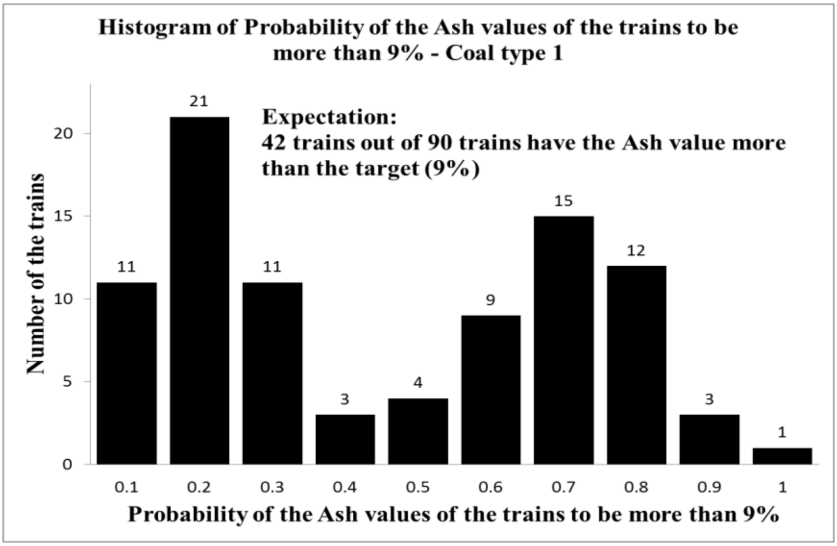

Figure 4.17. Histogram of probabilities of the ash content of trains for the coal type 1 to be more than 9%.

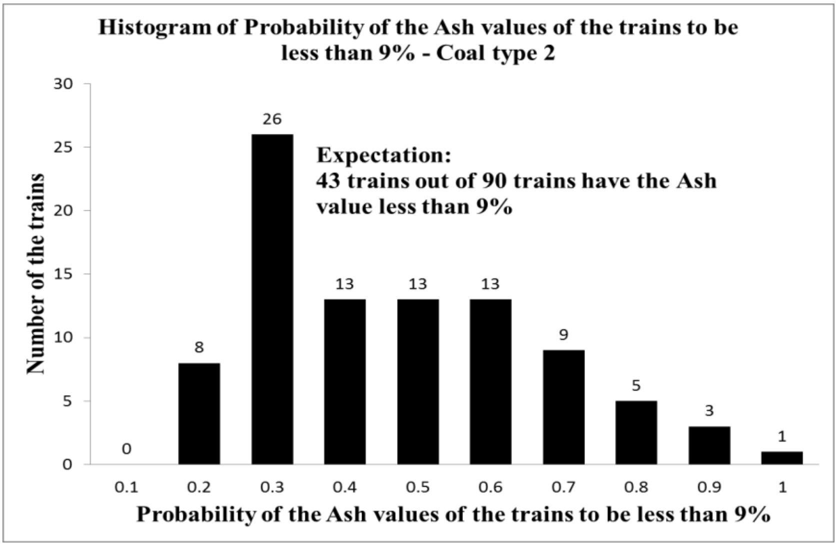

Figure 4.18. Histogram of probabilities of the ash content of trains for the coal type 2 to be less than 9%.

Previous examples illustrated that stochastic system simulation is a valid and powerful tool to explore the effects of geological uncertainty and unscheduled breakdowns on the expected performance of complex continuous mining systems.

It provides the mine planning engineer a valuable tool to foresee critical situations affecting the continuous supply of raw material to customers and the system performance.

4.4. CONCLUSIONS

Continuous mining systems require large investments and operational costs. Decisions in daily production scheduling are impacted by uncertainties, such as incomplete knowledge about the deposit and operational downtimes. These can have a significant influence on the actual production performance. This chapter proposed a simulation-based framework, where the method of geostatistical simulation has been integrated with mine process simulation to account for the effects of geological uncertainty and unscheduled breakdowns. The obtained results showed that such an approach provides the mine-planning engineer a valuable tool to foresee critical situations affecting the continuous supply of raw material to the customers and the system performance. It has been found that:

- Relying on the estimated model would indicate a biased and optimistic prediction of the ash content. This is due to ignoring the in-situ variability and the geological uncertainty. Histograms of multiple replications also illustrated this finding.
- The geological uncertainty does not only affect the amount of coal produced, but also affects waste management and downtimes due to dispatching.
- The range of uncertainty can be mapped by stochastic predictions. These predictions are based on realizations of the reserve block model.
- The average of the realizations showed a similar behaviour to reality.
- For this case study, the results illustrated that the ash content of more than 50% of the delivered trains deviated from the specified target. This will incur opportunity costs and economic losses due to the penalties.

5

SIMULATION MODELING – REAL-SIZE CASE STUDIES

The contents of this chapter have been adapted from:

Shishvan, M. S., & Benndorf, J. (2017). Operational Decision Support for Material Management in Continuous Mining Systems: From Simulation Concept to Practical Full-Scale Implementations. *Minerals*, *7*(7), 116. doi: 10.3390/min7070116.

5.1. Introduction

Chapter 4 demonstrated the implementation of the simulation approach for the quantification of the effects of geological uncertainty on achieving short-term production targets in a lab environment (TRL 4 was achieved). This chapter extends the developed simulation model to a new technology readiness level (TRL 6) by implementing it in an industrially relevant environment. A framework for modeling, simulation, and validation of the simulation model of a large continuous mine is presented in detail. Operational implementation issues, experiences, and challenges in practical applications are discussed. Furthermore, the strength of the application of simulation modeling as an operational decision support for material management in continuous mining systems is demonstrated. Material management in such systems is concerned with planning, organizing, and control of the flow of materials from their extraction points to destinations. Its aim is to get the right quality and quantity of materials at the right time and the right place at the lowest cost. This can be strongly affected by operational decisions that have to be made during the production process.

5

The framework is implemented and validated in two large coal (lignite) mines. The details of the case studies were already specified in Chapter 2. Results of both case studies are used to describe the details of the framework, and to illustrate the strength and limitations of its application.

The first section defines the goal and objectives. It will then go on to practical implementation by laying out the steps of building a simulation model and validating it, and discussing the obtained results. The last section concludes the findings of this chapter.

5.2. Goal and Objectives

This chapter aims to extend the developed simulation model in the previous chapter to a new level (TRL 6) by implementing and validating it in two large coal (lignite) mines.

Achievement of this goal involves the following objectives:

- Define the problem to be studied, constraints, and the type of analysis to be performed; (already defined in Chapter 2)
- Abstract the system into a model described by the components of the system, their characteristics, and their interactions;
- Identify, specify, and gather data in support of the model;
- Extend the existing simulation model with respect to the new problem, model, and data structure;

- Embed the simulation model in a simulation platform;
- Design some experiments for the purpose of verification and validation of the simulation model;
- Analyze the simulation outputs to draw implications and make recommendations for problem resolutions.

Having defined the goal and the objectives, the chapter will continue by stating the framework, which is based on the steps of a simulation study (see Section 3.4), to achieve the objectives.

5.3. PRACTICAL IMPLEMENTATION – METHODOLOGY

This section describes the framework of modeling, simulation, and validation of the simulation model of large continuous mining operations in detail. The proposed extended simulation model is intended to reproduce operational behavior in full-scale considering material management. For demonstration purposes, two case studies have been defined. The first case study is the Hambach mine and its main focus is on material management. The second case study is the Profen mine. In addition to material management, this case also focuses on coal quality management. The following section will discuss the conceptualization of the system under study.

5.3.1. CONCEPTUAL MODEL OF CONTINUOUS MINING SYSTEMS

The process of a continuous mining system can be divided into three sub-processes, see Figure 5.1. The operation starts with the excavation of materials by BWEs. It continues by the transportation of the extracted materials from mining benches to dumping benches or coal stockpiles. The transportation process includes a network of conveyor belts consisting of face conveyor belts, main conveyor belts, and a mass distribution center. Finally, lignite is stacked at the stockpile or waste materials are dumped at the waste dump.

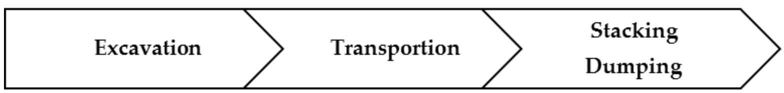

Figure 5.1. The sub-process of the continuous mining system.

The extraction and the transportation processes of materials can be emulated in a combined discrete-continuous stochastic environment. This provides the possibility to recreate the deterministic and/or random occurrences of events such as operating stoppages, which are caused by unavailability of spreaders or conveyor belts, equipment failures, and preventive/corrective maintenance activities.

As in the previous chapter, KPIs will be used to evaluate the success of the simulation model. Based on the different focus points of two case studies, the measured KPIs are as follow:

- Case Hambach: The quantity and the utilization KPI will be measured.
- Case Profen: All three KPIs will be measured.

5.3.2. Data Collection and Modeling of Stochastic Behavior

This section highlights the data that are required for building the simulator. The data are divided into three major groups including process related, elements related, and geological data, see Table 5.1. In our case studies, the process related and geological related data were easy to obtain. These are provided by the both industrial partners. Fortunately, both mines have their own SQL-based databases. The elements related data can be extracted from their databases. They keep almost all operational data including:

- Any data that is related to the production process, e.g., amounts of waste or coal and quality parameters of the delivered coal to different customers;
- Any data that is related to the breakdown of equipment, e.g., at what time the failure happens, what is the root cause, and the duration of the failure (i.e., the repair time).

The first group of data will be used to verify/validate the simulation model. Among the second group, in this study, mechanical, electrical, conveyor system, and operational failures are encountered to be the most crucial failures. The historical data of these failures are processed as shown in Figure 5.2. The analysis involves the identification of theoretical distributions that represent the input data. Arena® software facilitates the identification process by the *Input Analyzer* tool. After the theoretical distributions are fitted to the data, any data values from the theoretical distributions may represent the failure behaviors. However, a possible weakness of this approach is that a theoretical distribution may periodically generate an unusual value that might not actually ever be present in the real system. This issue will be elaborated in the validation section with an example.

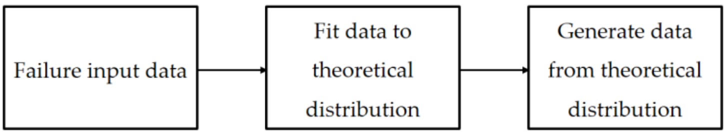

Figure 5.2. Procedure of processing failure input data (Chung, 2003).

Table 5.1. The required data for building a simulation model.

Process Related Data	1) Production targets (Daily/Weekly/Monthly/Yearly) a. Target tonnages and volumes for coal and waste b. Target coal quality c. Daily/Weekly schedules 2) Equipment a. Numbers and models b. Interdependencies between equipment c. Connected conveyor belts 3) Production system scheme a. Conveyor belts network and interdependencies b. Configuration of the mass distribution center (distribution options) 4) Stockpiles a. Locations and capacities (division in sub piles/packets) b. Associated conveyor belts c. Stacker and reclaimer capabilities 5) Sensors a. Position and type of measurements b. Frequency, accuracy, and precision
Elements Related Data (for Each Piece of Equipment)	1) Capacities of Excavators and Spreaders a. Effective b. Theoretical c. Effective capacity for different material types d. Failure characteristics (reliability/ availability) e. Mean time between breakdowns and repair times 2) Conveyor Belts a. Capacity (volume/hour) b. Belts lengths c. Belts profiles d. Speed e. Failure characteristics (reliability/ availability) f. Mean time between breakdown and repair time 3) Cycles of equipment a. Long cycle: time between two displacement of conveyor belt b. Block cycle: required time for extracting/filling one block c. Slice cycle: required time for extracting /filling one slice and getting ready for starting second slice. 4) A complete database of downtimes of the equipment.
Geological Related Data	1) A geological 3D-cell model

5.3.3. MODEL BUILDING—PROBLEM TRANSLATION

The main logic is designed based on the pervious sections, the conceptual model of a continuous mining system and the design of the model. Its flowchart is shown in Figure 5.3. In summary, a simulation begins with creating entities at minor intervals. As an entity arrives into the system, statuses of the assigned excavator and spreader are checked. In case of unavailability of one of them, the entity is disposed at the very beginning step. If both are active, it reads the data file and assigns the values to the correspondence attributes. These attributes consist of excavator number, bench information, conveyor belt number, block number, material type, volume, quality parameters, and the destination of the entity. Based on the material type, other type of attributes such as “time now” and “extraction time” are assigned on the way to the excavator. An entity has an “extraction time” attribute that corresponds to the delay that the entity should have in the excavator (a *resource* module in Arena®).

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The amount of the delay is equal to the time, if the excavator excavates the same amount of material in the reality. So, entity’s extraction time can be calculated using Equation (5.1) (the unit is minutes):

$$\text{Extraction Time} = \frac{(60\ \times\ \text{Entity volume})}{(\text{Theoretical capacity of the BWE } (\text{m}^3/\text{h}))}. \tag{5.1}$$

It should be noted that a “seize, delay, and release” resource module is used to imitate the excavation operation in the model. With this in mind, if the excavator and the spreader are still active, the entity is forwarded to seize in the resource module (the excavator). There, it has a delay as much as the extraction time attribute. After releasing the entity from the resource module, some statistics are recorded such as total waste volume, the total volume of each material type, total coal tonnage entering the system, and the weighted average of quality parameters (e.g., ash, calorific value). Thereafter, the entity is transported using a network of conveyor belts. When it reaches its defined destination, either dump site or coal stockpile, it passes the defined resource module. Here, also, some statistics are recorded such as the amount of different dumped/stacked materials. At the end, the entity leaves the simulation model by a dispose module.

As mentioned earlier, the model keeps track of some variables of interest during the simulation run. These variables are written in a text file at user-defined intervals.

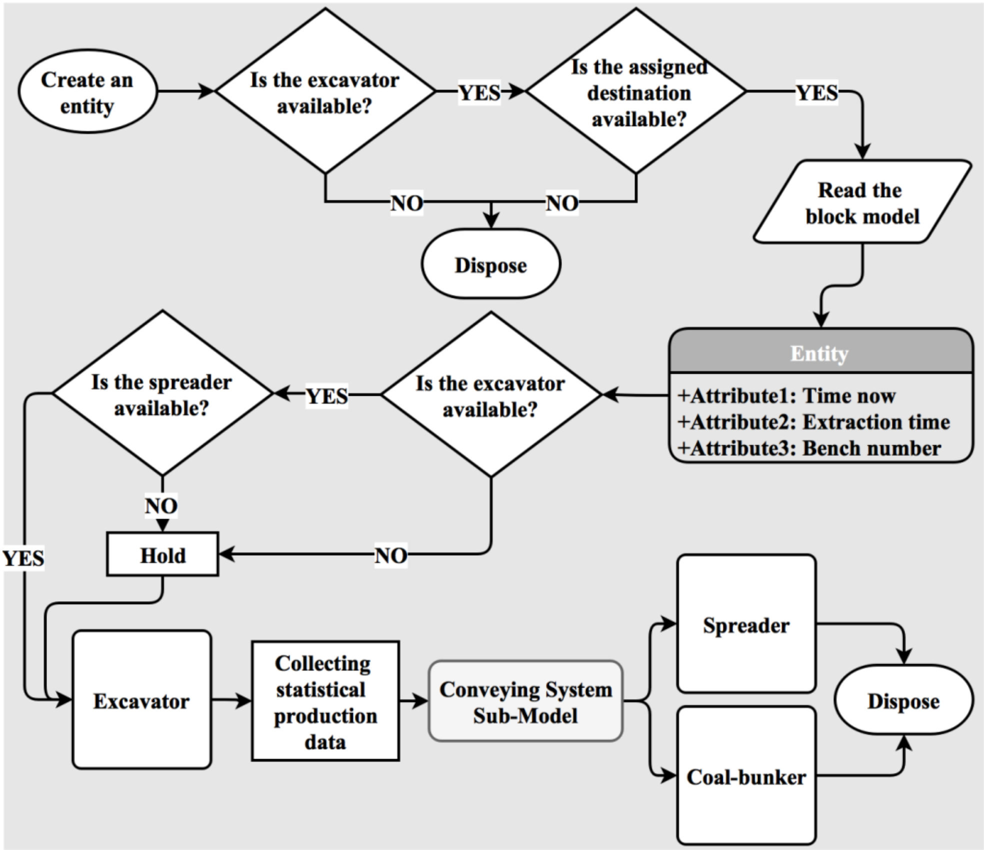

Figure 5.3. Flowchart of the main logic behind the simulation model.

5.3.4. Embedding the Simulation Model into a Simulation Platform

To achieve maximum flexibility of the simulation model and as a preparation for the next steps in this research, the mine simulator is embedded into a simulation platform. In this platform, the simulator is used to estimate the evaluation function. All the simulation preparation and post processing are done by several Python scripts, which are all controlled by the central controller script.

5.3.4.1 Simulation Platform Overview

Figure 5.4 shows the simulation platform with its different processes. It also shows the relationship that processes have with each other. There are three relationships:

- Control: The process controls another process, either via calling it with command line arguments or by using a programming interface.
- Read: The process reads information from a file and uses this for its processing.
- Write: The process writes information or results to a file, which either can be read by another process or is meant as an output to the user.

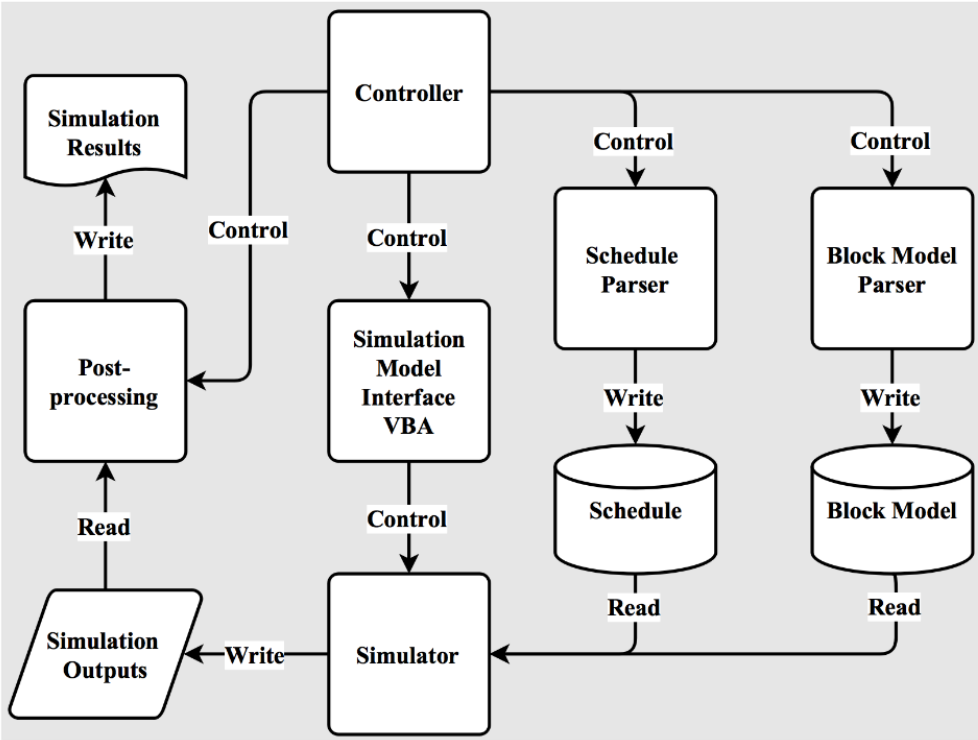

Figure 5.4. Simulation platform diagram.

The run of a single simulation can be described as four tasks, each containing their own subtasks that are often handled by different scripts, all initiated by the controller. The flow of a simulation run:

- Simulation configuration
  - The controller stores the date to be simulated and the output directory in a configuration file.
- Simulation preparation
  - The controller creates or clears the simulation output directory.
  - The block model parser selects the blocks to be used for the simulation and writes them to a database.

  - The schedule parser creates a schedule based on the weekly/monthly schedule of the mine and writes the schedule to a database.
- Simulation run
  - The controller calls the simulation model interface, which in turn instructs Arena to load the desired simulation model, reload the schedule data and then to run the simulation.
  - Arena reads the block model and schedule data from the databases, runs the simulation and writes the output to the simulation output files.
  - The controller copies the Arena output files to the output directory.
- Simulation post-processing
  - The post-processing script generates the tables and figures that show the simulation results.

A process worth attention is the simulation model interface, which is situated between the controller and the simulator. This process is required because there is no direct way to interact with the simulation software using for example the command line. Instead, the program relies on automation via Visual Basic for Applications (VBA), a technology for creating interconnection between applications. This technology is not available in Python, thus the simulation model interface is written in Visual Basic and compiled as an executable that can be run from the command line with the relevant parameters. The VB script will wait until the simulation run is complete and then exit, at which the controller knows that the simulation is finished.

5.3.4.2 POST-SIMULATION PROCESSING OF RESULTS

There are four main files created by the simulator:

1. Coal-bunker output for all excavators and replications, one line per entity;
2. Waste dump output for all excavators and replications, one line per entity;
3. Aggregated volume statistics per excavator;
4. Detailed activity log of excavators.

The coal and waste files contain the important parameters for each entity that leaves the system, the disposal time, and the replication number. The processing of these files contains the following steps:

- split the data per replication and resample the different entities,
- sum them up by day (for an example),
- determine the weighted average of quality parameters, and
- write the values in a file with the following order: replication, date, values.

The post-processing then creates various plots that give an overview of the performance of the simulation. For coal and waste, both the mean production and the uncertainty of the daily production are plotted. The uncertainty is used as a *P10* minimum and *P90* maximum value. These values are obtained by sorting the values of the different replications ascendingly and then taking the value at index *N*0.1* for the *P10* and *N*0.9* for the *P90*, where *N* is the total number of replications.

For the quality parameter, the plotting is slightly different. Since there are 25 different simulated ash values, the calculation will take the value of quality simulation i for replication i. The *P10* and *P90* values are then calculated in the same way as for the production volume. The estimated ash values are also plotted to be compared with the simulated the values.

5.3.5. Design of Experiments for Validity Test of the Case Studies

To evaluate the validity of the simulation model, a set of numerical experiments was designed. The strategy for designing experiments follows three major objectives. The first objective is to show that the simulation model reproduces observed data of the real system, when historic deterministic input is provided. The second objective is to demonstrate the strength of the simulation model when 'breakdown behavior' as a stochastic component is added, (the utilization KPI). The third objective is to quantify the effects of geological uncertainty and reconcile its results against measured KPIs observed in reality. The first two objectives are pursued in the both case studies but the last objective is sought only in the Profen case. With these in mind, experiments are designed as follows:

- Experiment 1: Run the simulation model without stochastic components
    - The input reserve block model is derived from actual measured data. Other parameters such as working schedule, failures, and excavation rates are taken as historically performed, deterministic values.
    - The target of this experiment is to verify the output of the simulation model against what happened in the mine during the time horizon considered.
- Experiment 2: Run the simulation model with stochastic component "breakdown behavior"
    - The reserve block model is kept as in Experiment 1 and it represents reality. In this experiment, theoretical distributions for predicting unscheduled breakdowns of equipment are added to the model as stochastic components.
    - The target of this experiment is to test the reliability of the model in predicting downtimes. The utilization KPI is measured.
- Experiment 3: Run the simulation model with stochastic components "breakdown behavior" and "reserve block model"

- This experiment is designed for the quantification of geological uncertainty in the Profen mine. After being certain that equipment failure models are good enough, the stochastic input “reserve block model” is added to the simulation model. In total, there are 26 different reserve block models (different possible values for ash content) as mentioned earlier.

5.4. Results and Discussion

The following section presents results of the experiments. It should be noted that for both case studies, three months of production data are used to validate the simulation models. However, only the part of the results that emphasizes the practical implementation issues and challenges are presented.

5.4.1. Case Profen

5.4.1.1 Experiment 1: Simulation Model without Stochastic Components

Table 5.2 provides the summary statistics of simulated and actual production data with the calculated evaluation measures. Closer inspection of the table shows that the difference for the mined coal quantity is very close to zero and no difference greater than 4% was observed. In addition, it is apparent that the average relative error per day displays higher values. These values are rather counterintuitive. A possible explanation for this is due to high variability, as there are significant deviations on a short-term (daily) basis. However, on average, the prediction of coal quantity is good.

Table 5.2. Summary statistics of simulated and actual production data of the Profen case, Exp. 1.

Material Type	Simulated	Actual	Difference (%)	Bias (m^3or t)	Average Deviation (m^3or t)	Average Relative Error per Day (%)
Coal (10^3 t) *	533.01	533.06	−0.01	−0.05 *	5.02 *	26.30
Waste (10^3 m^3)	1336.28	1378.03	−3.03	−41.75	10.66	23.62
Total (10^3 m^3)	1794.81	1841.56	−2.54	−46.74	8.49	15.25

* The unit is tons.

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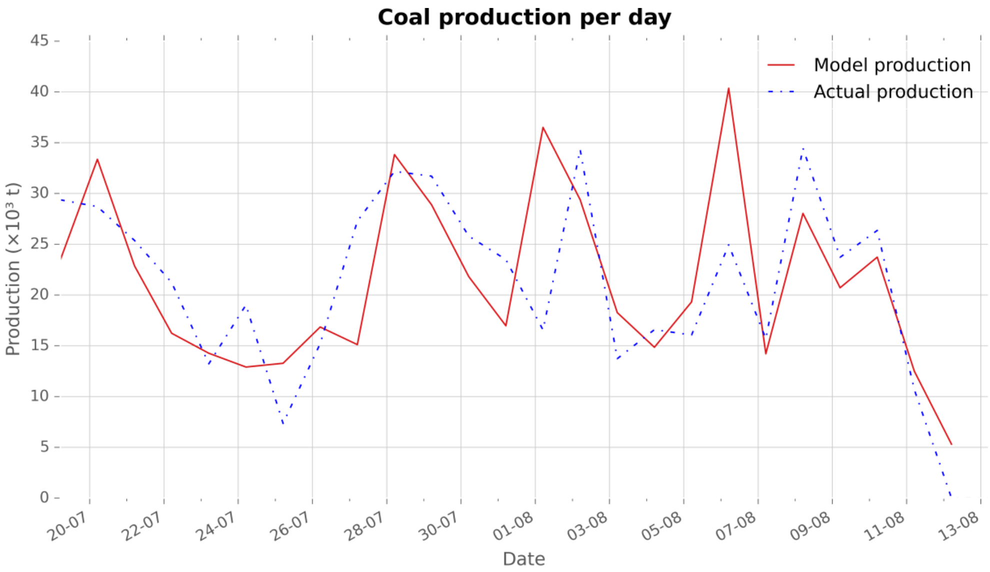

Figure 5.5. Comparison of daily production of coal, Experiment 1.

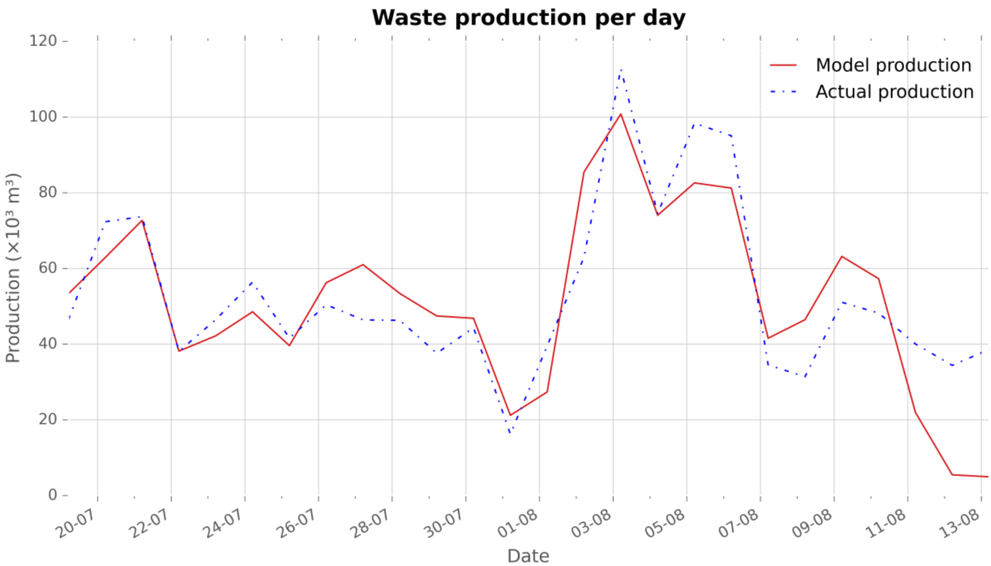

Figure 5.6. Comparison of daily production of waste, Experiment 1.

Furthermore, for the given time horizon, the graphs of the daily production of coal and waste are shown, respectively, in Figure 5.5 and Figure 5.6. What stands out in the figures is that the output of the simulation model (model production) is well correlated with the actual production of the mine. Taken together, these results indicate the verification of the simulation model with all deterministic inputs against the real system.

5.4.1.2 EXPERIMENT 2: SIMULATION MODEL WITH STOCHASTIC COMPONENT "BREAKDOWN BEHAVIOR"

In this experiment, theoretical distributions of failure models related to equipment breakdown behaviors are added to the simulation model. The number of simulation replications was set to 20 as recommended in Section 4.1.6. The obtained results are presented in Table 5.3. It is clear from the table that following the addition of the stochastic components, significant increases in the average deviations and average relative errors were recorded. However, increments in the differences (sum of over/under production in the given time horizon) were not statistically significant (less than 2%). Further investigation showed that an unusually long breakdown of one piece of equipment happened in situ during the study time horizon. Not surprisingly, the historical failure data show that the probability of an occurrence of such a long lasting failure is very low. Nevertheless, such circumstances are unavoidable due to the stochastic nature of unscheduled breakdowns.

Table 5.3. Summary statistics of simulated and actual production data of the Profen case, Exp. 2.

Material Type	**Simulated**	**Actual**	**Difference (%)**	**Bias (m^3or t)**	**Average Deviation (m^3or t)**	**Average Relative Error per Day (%)**
Coal (10^3 t) *	541.96	533.06	1.67	8.90 *	10.36 *	62.55
Waste (10^3 m^3)	1373.68	1378.03	−0.32	−4.34	20.19	47.22
Total (10^3 m^3)	1844.95	1841.56	0.18	3.39	24.08	40.76

* The unit is tons.

Additionally, the daily production graphs of coal and waste are presented, respectively, in Figure 5.7 and Figure 5.8. The dashed line shows the actual production, the solid line shows the average of simulation replications, and the dark shadow part demonstrates the predicted range of uncertainty (area between 0.10 and 0.90 quantile) introduced by the stochastic breakdown behavior. The single most striking observation to emerge from the figure is the negative correlation between the simulated and the actual production in two parts of the graphs. As discussed earlier, an unusual long breakdown happens in the beginning of the time horizon (21.07–25.07), which is not predicted by the failure models. Therefore, the simulation continues the production process while in the reality the production is decreased.

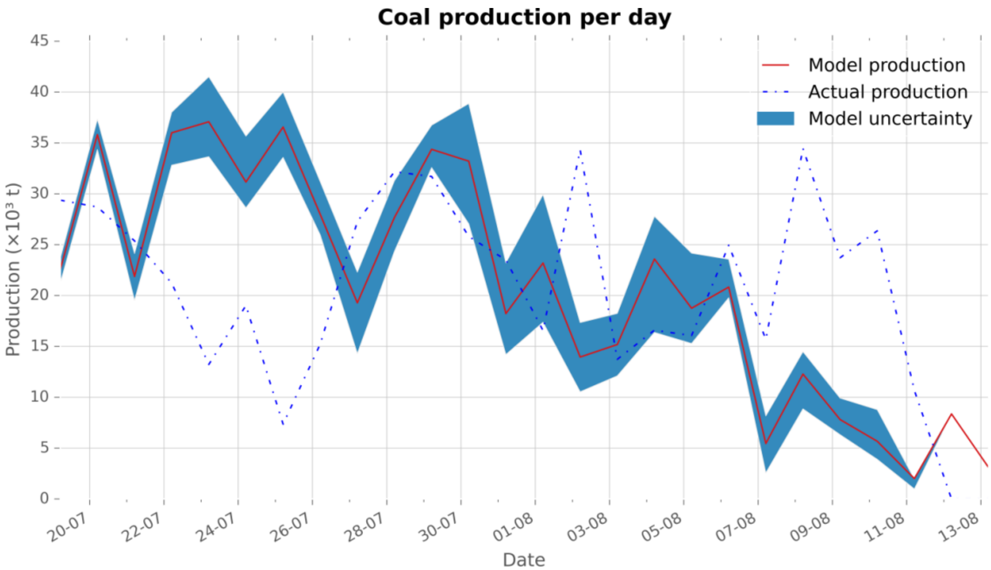

Figure 5.7. Comparison of daily production of coal, Experiment 2.

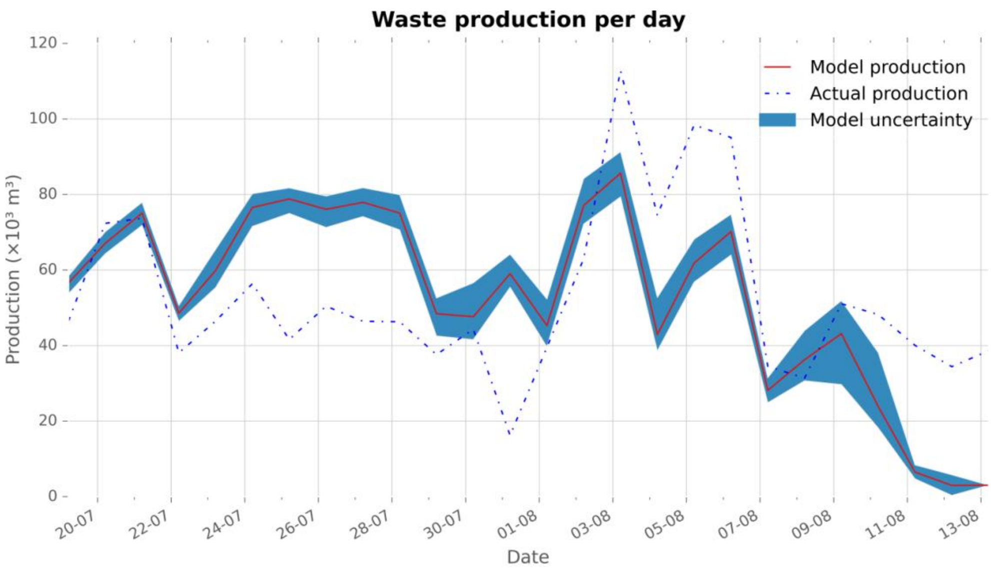

Figure 5.8. Comparison of daily production of waste, Experiment 2.

In addition, a closer look at the graphs shows another negative correlation at the end of the time horizon. This behavior surfaced mainly in relation to the first issue. It is a natural behavior if at the end of the period a shortage is observed due to the overproduction at the beginning. The argument is valid for both coal (Figure 5.7) and waste (Figure 5.8) graphs in the figure. For the middle period, the average of simulations and the actual production are positively correlated. There are some differences, but differences are inside the uncertainty range.

The second objective of this experiment is to demonstrate the reliability of the simulation model in terms of the utilization KPI. Table 5.4 summarizes the utilization KPI predicted by the simulation model. Table 5.5 presents the actual utilization. Differences between the actual and the simulated utilization are given in Table 5.6. In the presented tables, the status "Busy" means the excavator is digging materials, "Failed" means the excavator stopped working (e.g., due to a failure), "Idle" means the excavator is neither digging nor failed (e.g., transportation), and "Inactive" means the excavator is not working (e.g., due to the periodic maintenance or planned downtime).

Table 5.4. Utilization predicted by the simulation model.

Status	Bg.1580	Bg.1511	Bg.1553	Bg.351	Bg.1541	Bg.309
Busy	14.3%	49.8%	46.1%	60.5%	57.8%	27.6%
Failed	1.0%	4.7%	1.7%	3.7%	1.1%	0.6%
Idle	-	7.8%	37.0%	3.7%	8.5%	7.4%
Inactive	84.7%	37.7%	15.3%	32.3%	32.5%	64.5%

Table 5.5. Actual utilization of the system.

Status	Bg.1580	Bg.1511	Bg.1553	Bg.351	Bg.1541	Bg.309
Busy	11.7%	54.0%	44.7%	55.8%	56.7%	28.2%
Failed	2.9%	6.9%	40.9%	10.9%	14.8%	7.1%
Inactive	85.4%	39.1%	14.4%	33.3%	28.5%	64.6%

Table 5.6. Differences between the actual and model utilization.

Status	Bg.1580	Bg.1511	Bg.1553	Bg.351	Bg.1541	Bg.309
Busy	2.6%	−4.2%	1.4%	4.7%	1.1%	−0.7%
Failed	−1.9%	−2.2%	−39.2%	−7.2%	−13.7%	−6.6%
Inactive	−0.7%	−1.4%	0.8%	−1.0%	4.1%	−0.2%

The range of differences for busy status (operating time) varies between −5.7% and 4.7% in the time horizon of three months. Statistically, it can be an acceptable range. As noted earlier, the simulation of a continuous mine is a complex problem and there are a lot of influencing factors. These results underline the validity of probability distributions that are used for the prediction of unscheduled breakdowns. However, it should not be forgotten that cases such as the breakdown of Bg.1553 could happen, though they represent outliers. They are unavoidable and sometimes unpredictable due to the stochastic nature of unscheduled breakdowns.

5.4.1.3 EXPERIMENT 3: SIMULATION MODEL WITH STOCHASTIC COMPONENT "BREAKDOWN BEHAVIOR" AND "RESERVE BLOCK MODEL"

The third experiment is the most comprehensive test. The statistics are summarized in Table 5.7. As it can be seen, the difference between the simulated and the actual production are 10.24% for coal and 1.54% for waste. In this experiment, differences are higher compared to the pervious experiments. This is expected due to the uncertainty associated with the reserve block model. The sum of the produced coal and waste shows a difference of less than 3%, which is statistically an acceptable deviation.

Table 5.7. Summary statistics of simulated and actual production data of the case Profen, Exp. 3.

Material Type	Simulated	Actual	Difference (%)	Bias (m^3 or t)	Average Deviation (m^3 or t)	Average Relative Error per Day (%)
Coal (10^3 t) *	582.51	533.06	10.24	49.45 *	12.31 *	65.90
Waste (10^3 m^3)	1402.73	1378.03	1.54	24.7	16.33	29.29
Total (10^3 m^3)	1909.26	1841.56	3.49	67.7	18.82	24.65

* unit is in tonne.

To quantify the effects of geological uncertainty the average daily ash values are compared in Figure 5.9. The blue dashed-dot line shows the ash value of actual production, the red-dashedline demonstrates ash values of the estimated model, and the solid red line presents the average ash values of the simulations (realizations). The predicted range of uncertainty is illustrated by a dark shadow cloud in the graph. It is clear from the figure that the estimated model and the actual production are not well correlated. The estimated model has a tendency to underestimate ash values. This issue was discussed in the problem statement section.

What is striking about the graphs in Figure 5.9 is that the actual production data are well covered by the predicted range of uncertainty. Only at the beginning of the time horizon, some parts are outside of the range. As discussed earlier, a breakdown that is not captured by the failure models is the reason for this phenomenon.

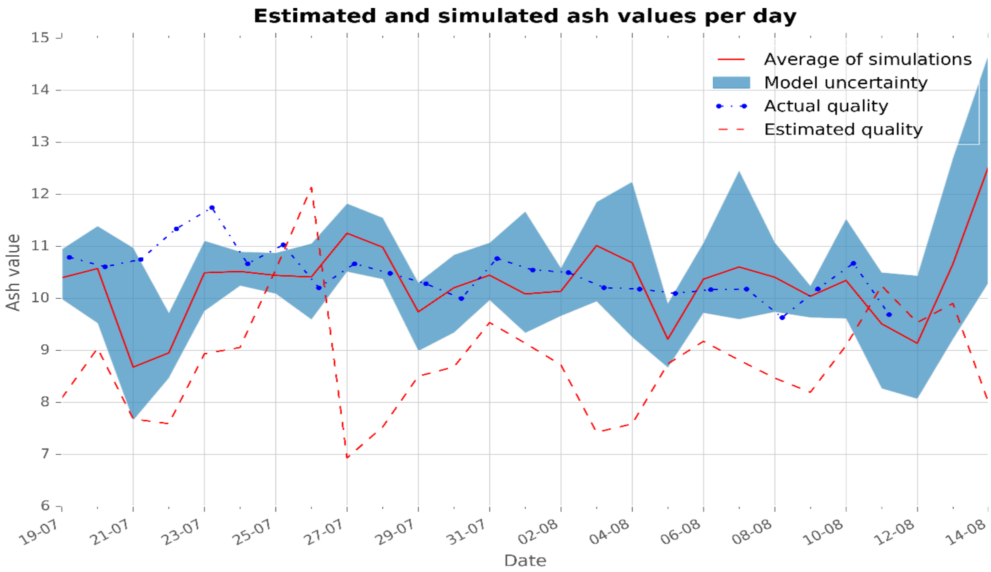

Figure 5.9. Daily ash values per day, case Profen.

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Similar to the previous experiments the total amount of daily production of coal and waste are shown, respectively, in Figure 5.10 and Figure 5.11. From the graphs a relatively good match can be seen. However, the inconsistency in the reserve block model causes some deviations. It can be seen that the quality of the historical data is the key factor to achieve good results.

Together these results provide important insights into the verification and the validation process of the simulation model of the Profen mine. Some important points are:

- A good prediction over long time frames.
- Deviations were seen on short time scales due to geological uncertainty.
- The occurrence of rare events may not be well captured in simulation experiments.
- In this case, for practical application, the model input would have to be adjusted according to the actual situation (e.g., equipment down for some timeframe) and iteratively re-run it.

Finally, an important implication emerging from these results is that the simulation model can effectively be used as a decision making tool. Impacts of the different decisions (e.g., different task schedules) can be assessed by the simulation model. The next section presents the validity test results of the Hambach case as a second case study.

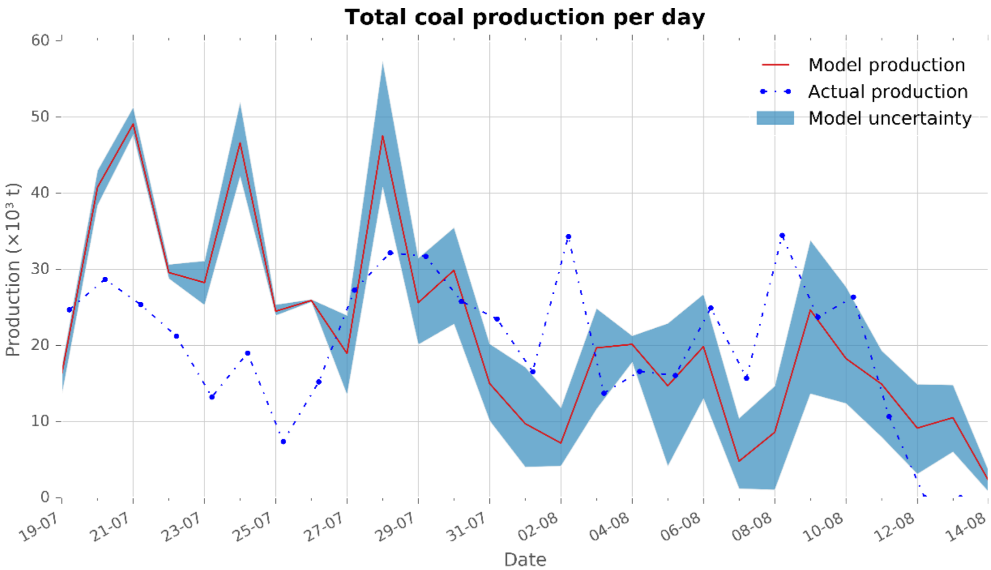

Figure 5.10. Comparison of daily production of coal, Experiment 3.

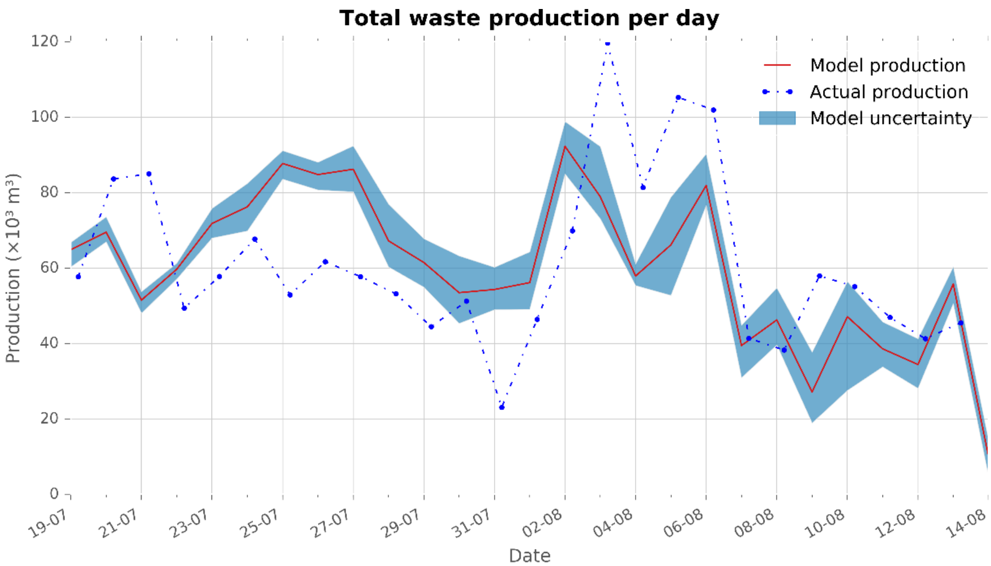

Figure 5.11. Comparison of daily production of waste, Experiment 3.

5.4.2. CASE HAMBACH

5.4.2.1 EXPERIMENT 1: SIMULATION MODEL WITHOUT STOCHASTIC FAILURE MODELS

Summary statistics of a monthly production with the calculated evaluation measures are presented in Table 5.8. What stands out in the table is that the total deviation is about 100,000 m^3, which is only 0.47% of the total production. To explain better, the total theoretical capacity of the equipment of the Hambach mine is about 86,000 (m^3/h). It denotes that the total deviation between the actual and prediction is slightly more than an hour of the production. Taken together, it can be seen that the simulation model imitates the reality with an acceptable precision.

Table 5.8. Summary statistics of the simulated and the actual production data of the Hambach case, Exp. 1.

Material Type [1]	**Simulated**	**Actual**	**Difference (%)**	**Bias (m^3or t)**	**Average Deviation per Shift (m^3or t)**	**Average Relative Error Per Shift (%)**
M1 (m^3)	10,604,266	10,655,819	−0.48	−51,553	26,178	0.25
M2T (m^3)	4,263,052	4,290,314	−0.64	−27,262	16,965	0.40
M2N (m^3)	2,765,828	2,765,928	0.00	−100	15,050	0.54
FOKI (m^3)	33,329	33,329	0.00	0	593	1.78
KIES (m^3)	16,000	16,000	0.00	0	251	1.57
Coal (t)	4,157,393	4,183,493	−0.62	−26,100	7872	0.19
Total volume (m^3)	21,297,599	21,399,210	−0.47	−101,611	27,064	0.13

[1] M1, M2T, M2N, FOKI, and KIES are abbreviations for different types of waste materials.

Furthermore, the total shift-based production of the Hambach mine during the test's time horizon is shown in Figure 5.12. The dashed-line shows the actual production and the solid-line presents the simulated production data. The presented graphs illustrate that the simulated data follow the actual production data with some deviations. As explained in the previous section, these deviations occur due to the existence of some inconsistencies in the reserve block model. .

Additionally, for different material types (e.g., M1, M2T, etc.) shift-based production graphs are presented in Figure 5.13. Closer inspection of the graphs shows that, with Coal (f), as an example, there is an analogous behavior between the simulated and the actual data. Overall, statistical measures such as the average deviation of about 27,000 m^3 and the average relative error of 0.13% per shift indicate the verification of the simulation model.

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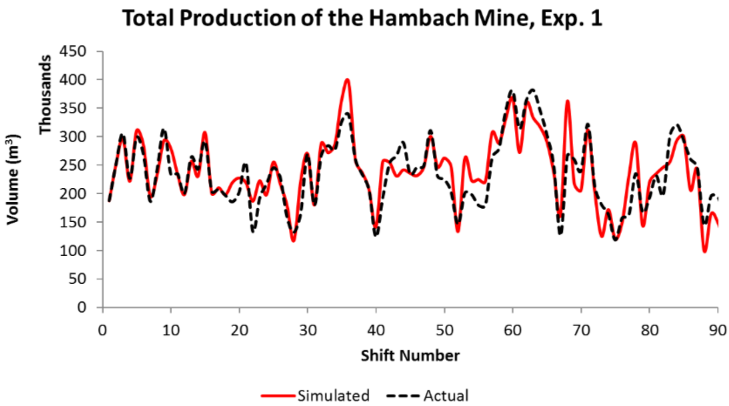

Figure 5.12. The total shift-based production of the Hambach mine, Experiment 1.

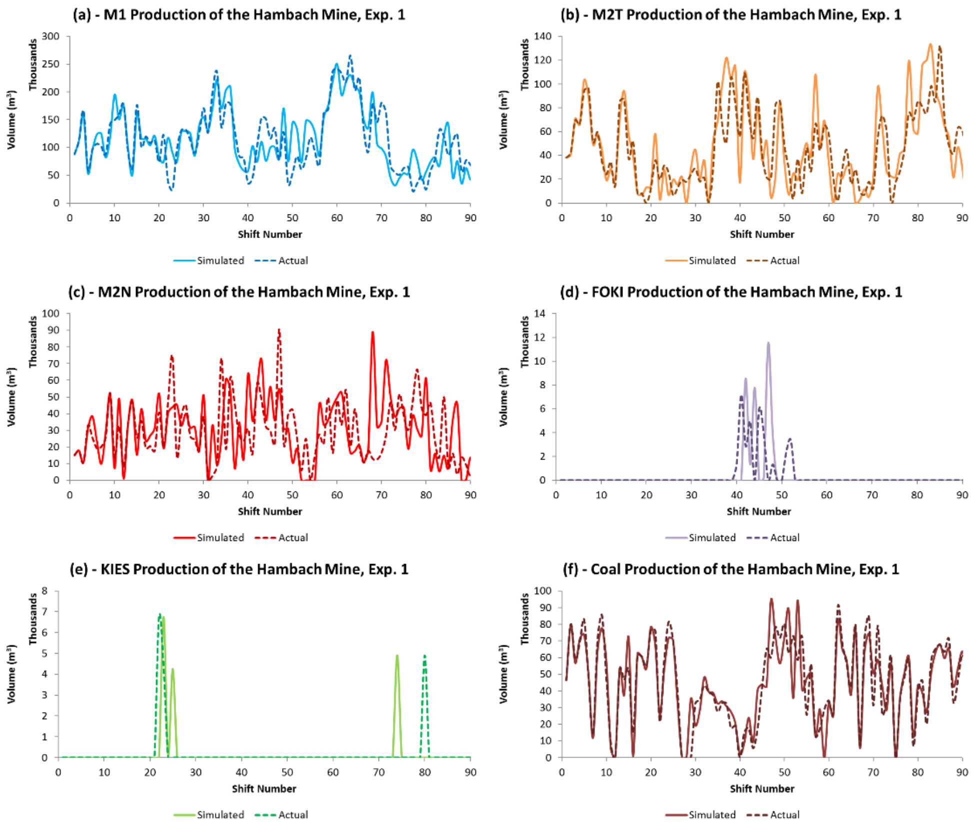

Figure 5.13. The shift-based production of different materials of the Hambach mine, Experiment 1.

5.4.2.2 *Experiment 2: Simulation Model with Stochastic Failure Models*

In this experiment, failure models are added to the simulation model. This experiment is specifically designed to show how reliable those models are. The summary and statistical measures of experiment 2 are presented in Table 5.9. Values in the simulated column of the table are the average values of 20 simulation replications. It is apparent that deviations are increased when comparing the results with Experiment 1. This is due to the addition of stochastic components to the simulation model. No significant difference between the actual and the simulated data is observed. The maximum difference occurs in the production of coal, which is equal to 2.9%. When considering the whole operation, a difference of 1.23% is recorded for a month of production. At a smaller scale, no difference greater than about 31,000 (m^3) per shift was observed.

Table 5.9. Summary statistics of the simulated and the actual production data of the Hambach case, Exp. 2.

Material Type [1]	Simulated	Actual	Difference (%)	Bias (m^3or t)	Average Deviation per Shift (m^3or t)	Average Relative Error Per Shift (%)
M1 (m^3)	10,556,753	10,655,819	−0.93	−99,066	27,892	0.26
M2T (m^3)	4,257,161	4,290,314	−0.77	−33,153	14,912	0.35
M2N (m^3)	4,257,161	4,290,314	−0.77	−33,153	14,610	0.34
FOKI (m^3)	33,329	33,329	0.00	0	414	1.24
KIES (m^3)	16,000	16,000	0.00	0	251	1.57
Coal (t)	4,060,603	4,183,493	−2.94	−122,890	9336	0.22
Total volume (m^3)	23,181,006	23,469,269	−1.23	−288,263	30,938	0.13

The total shift-based production for the given time horizon is presented in Figure 5.14. The dashed-line shows the actual production and the solid-line presents the average of simulation replications. Moreover, the dark cloud has been added to the graph as the predicted range of uncertainty (area between 0.10 and 0.90 quantile). From the figure, a good correlation between the simulated and the actual production data can be found. In addition, it is clear that the actual production is well covered by the shadow part.

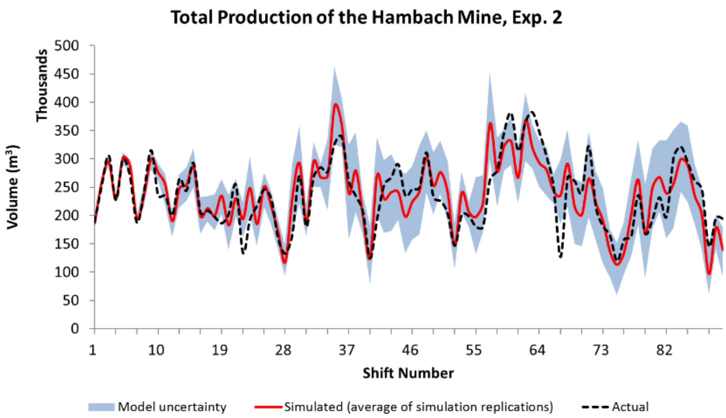

Figure 5.14. The total shift-based production of the Hambach mine, Experiment 2.

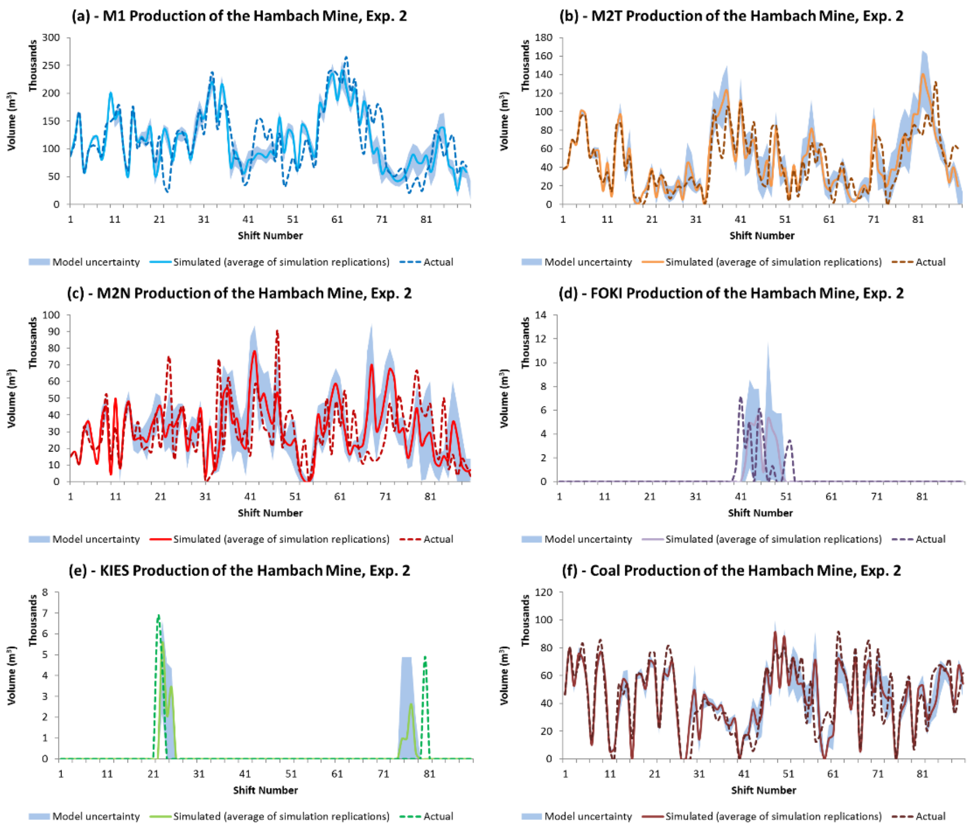

Figure 5.15. The shift-based production of different materials of the Hambach mine, Experiment 2.

Likewise, in Figure 5.15, a good correlation can be seen for the presented production data of different material types. However, it can be seen from this illustration that where there are a sufficient number of observations (Figure 5.15a–c,f), the actual and simulated values are well correlated, but where there are few data points, such as in Figure 5.15-d or Figure 22-e, the error between the simulation model's predictions and the actual data points is increased.

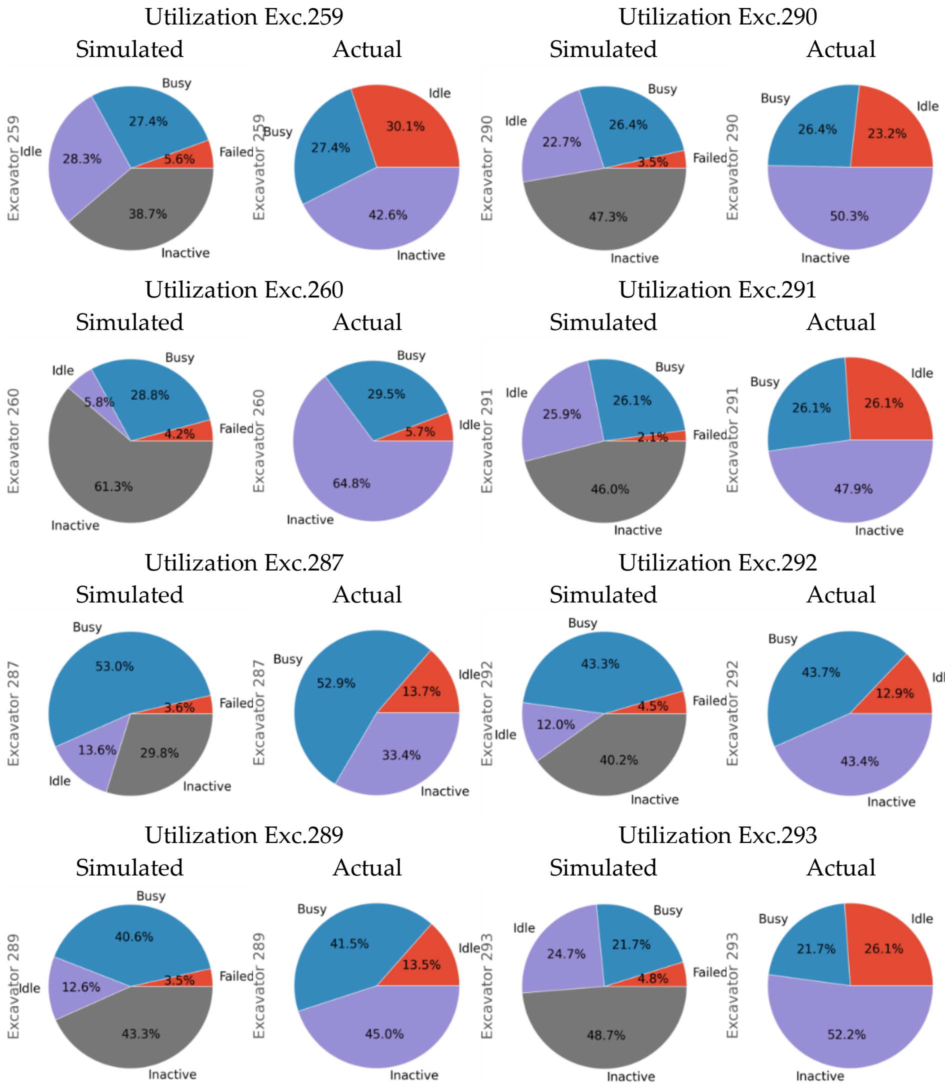

Figure 5.16. Utilization of the equipment in the form of pie charts.

As stated earlier, the utilization KPI is measured in Experiment 2. The results are presented in the form of pie charts in Figure 5.16. The "Busy", "Failed", "Idle", and "Inactive" statuses have already been defined in the previous case. For each excavator, two pie charts are given. One represents the actual utilization recorded at the mine and the other represents the simulated utilization by the simulation model. At the first glance, there are a number of similarities between the simulated model and the actual system. The most significant parameter that is very close to reality is the percentage of the busy hours. In most of the cases (excavator 259, 290, 291, and 293), these percentages are same. For the other excavators, no differences greater than 1% were observed. For a better clarification, 1% difference in a month (744 h) refers to only 7.44 h difference. From these results, it can be inferred that the failure models are good enough to predict breakdown behaviors of the equipment.

To summarize this section, the results show that, first, the simulation models (both cases) are verified/validated against the historical data. Second, the developed simulation models are reliable when the failure models (for the purpose of prediction of downtimes) are added to the model. An implication that can be drawn from the results is the possibility of using the simulation modeling approach as an operational decision support. The proposed method can also be applied in other research areas such as waste management or recycling of material excavated from tunnels (Entacher et al., 2011, Petitat et al., 2015). The next section concludes the main findings of this study.

5.5. Conclusions

Throughout this chapter, the developed simulation model in Chapter 4 has been extended to a new technology readiness level (TRL 6) by implementing it in an industrially relevant environment. A framework for modeling, simulation, and validation of the simulation model of a large continuous mine has been presented in detail. The framework was implemented in the two defined case studies. The case study approach was chosen to provide detailed illustrations of steps of a simulation study, implementation issues, and challenges in practical applications. A number of important practical implications emerge from this study:

- The quality of the historical data that are used for the calibration of the simulation model is very important.
- Experienced problem formulators and simulation modelers are crucial for a successful simulation study.
- The occurrence of rare events (e.g., long breakdowns of equipment) may not be well captured in simulation experiments.

The second aim of this chapter was to demonstrate the strength of simulation modeling as an operational decision support tool for material management. The relevance was clearly supported by the current findings. The results indicated that a validated simulation model could be used to assess the impacts of different scenarios (e.g., different task schedules) in the mine. Based on the type of analysis and the measured KPIs, the best scenario among all can be executed in the reality.

6

SIMULATION-BASED OPTIMIZATION – FULL-SIZE CASE STUDY

The contents of this chapter have been adapted from:

Shishvan, M. S., & Benndorf (2017). A Simulation-based Optimization Approach for Material Dispatching in Continuous Mining Systems. Under review at European Journal of Operational Research (EJOR).

6.1. INTRODUCTION

Short-term production scheduling of a continuous mining system defines a sequence of extraction and dumping operations over time within a predefined production plan. This schedule is concerned with the present operating conditions and constraints within the confines of the most recent long or medium-term plan. It plans extraction and dumping sequences in terms of weeks or days. The optimization of short-term production scheduling is conventionally performed in two distinct steps, (Hustrulid and Kuchta, 2006). The first step optimizes only the sequence of extraction of materials. The second step optimizes the dispatch decisions based on the dumping sequences, equipment capacity, performance, and availability. The focus of this study is on the second step of the optimization.

In the real world, there are limitations to the above mentioned distinct optimization steps, which may result in non-optimal or infeasible short-term production schedules (Matamoros and Dimitrakopoulos, 2016). First, uncertainty in input parameters is not considered in the optimization steps. Second, operational considerations and equipment availability are disregarded in the optimization of the extraction sequence of material, and thus can be unrealistic. Lastly, most of the mathematical programming approaches are limited by the amount of the decision variables. Indeed, simplifying assumptions should be made to develop a manageable mathematical model. The performance of the production scheduling can be unfavorably affected by above-mentioned limitations and this may lead to: (a) increased operating costs due to the unscheduled downtimes; (b) uncertainty in the performance of equipment and lower utilization of equipment; and (c) inability to meet expected production targets. This dissertation proposes a new simulation-based optimization approach that can accommodate these limitations. This approach consists of running alternatingly a deterministic optimization model and a stochastic simulation model. It uses a staged top down approach by combining simulation, the transportation problem, and the job-shop scheduling problem. The transportation problem provides a mechanism to optimize dispatch decisions. In other words, it finds optimal connections between excavators and spreaders. Because of the nature of the transportation problem, it is possible to have multiple connections for an excavator. Therefore, the job-shop scheduling problem deals with the allocation of spreaders to different excavators over time. Its objective is to find the processing sequences and starting times of each operation on each spreader, in order to minimize the total weighted tardiness. Finally, the system simulation uses the dispatch decisions generated by optimization and evaluates particular performance indicators under uncertainty in system performance. The calculated values are then introduced into a control module. The control module suggests refinements to parameters of the optimization model (e.g. transportation costs, jobs order, and jobs weight). The iterative process ends after a stopping criterion is met. The proposed approach is tested on a large continuous mine under different given dumping sequences, and results are reported. The merits and limitations of the proposed approach as pinpointed and farsighted operations management are discussed.

A considerable amount of literature has been published on the optimization of short-term production scheduling. These studies in early attempts have focused on evolving concepts and related formulations for finding extraction sequences based on mathematical programming, e.g. (Wilke and Reimer, 1977, Wilke and Woehrle, 1980, Gershon, 1983). Their objective is to minimize production deviations from the long-/medium-term production targets. While allocating resources, the conventional optimization process considers mining direction and fleet capacity. Nevertheless, it does not integrate the fleet management, i.e. dispatching of mining equipment and uncertainty in equipment availability. More recent attentions thus focus on the provision of real-time fleet allocation for short-term production scheduling (Alarie and Gamache, 2002, L'Heureux et al., 2013) and stochastic optimization of short-term production scheduling (Topal and Ramazan, 2012, Matamoros and Dimitrakopoulos, 2016). They have been successfully applied for over three decades to find optimal solutions for real size case studies. However, a large and growing body of literature has mainly investigated the applications that are in the discontinuous block mining with the diffuse deposits.

In the following sections, a brief background about the production planning of continuous mining systems will be given. It continues by defining the problem. Then, the solution strategy is discussed in detail. After that, the computational framework and its implementation are presented. The Hambach mine (Case 2) is used to demonstrate the performance of the proposed approach. Finally, the obtained results are reported. The last section concludes the findings of this chapter.

6.2. BACKGROUND

In continuous mining systems, usually known as opencast mines, the excavators can be seen as supply points and the spreaders together with the coal-bunker can be considered as demand points.

The production planning in an opencast mine covers various periods, namely long-, medium-, and short-term planning horizons. The long-term planning affects an opencast mine across its entire life, all the way to the end of mining supervision after the land reclamation. The medium-term planning often covers the next five-year period. Finally, the short-term planning is a yearly seam-focused detailed plan.

Besides operational and economical parameters that are necessary for any production planning process, the major input here is the geological block model. It is divided to two separate block models namely, the extraction block model and the dumping block model. The former includes the geological strata, quality parameters, volumes-tonnages, and material types. The latter includes dumping profiles and volumes.

As mentioned earlier, the short-term plan is guided by medium and long-term plans. Forasmuch as the complex deposit formations require selective mining of coal as well as overburden on different benches. The objective of short-term planning is to find the sequence of blocks, known as the extraction sequence, that meets the defined targets under current operating conditions and constraints. After the creation of the extraction sequence, the first step of the optimization of the short-term scheduling is completed. The created extraction sequence can be used as a guide to create the dumping sequence. It is also an input for the second step of the optimization procedure, which is the focus of this dissertation. The next section describes the problem with the defined objectives.

6.3. Problem Description

Figure 6.1 presents a flow diagram of the short-term production scheduling process in continuous mining systems. Three major processes can be seen in the diagram namely, short-term planning, dumping sequence creation, and material dispatching. These should be completed in the presented logical order to have a short-term schedule. Here, there are two underlying assumptions; the first is that the extraction block model, the dumping block model, and the extraction sequence are given as discussed in the previous section. Stable dump construction needs different material types with special sequences; while these materials are distributed unevenly at the extraction side, the second underlying assumption becomes very important. It is defined as that the problem should be relatively a balanced problem. In a sense, the difference between the total amounts of different overburden materials at the extraction site with the amounts of available spaces at the dumping site should be a small number. In the presence of finite available space for a material type, when the extraction of that material type becomes sufficiently large, then for any given dumping sequence it will no longer be possible to meet the defined production targets. The optimization of dispatch decisions thus must involve the dumping capacity constraints. Furthermore, uncertainty is associated with input parameters, equipment availability, and their performances, and the resulting problem is therefore a constrained stochastic optimization problem.

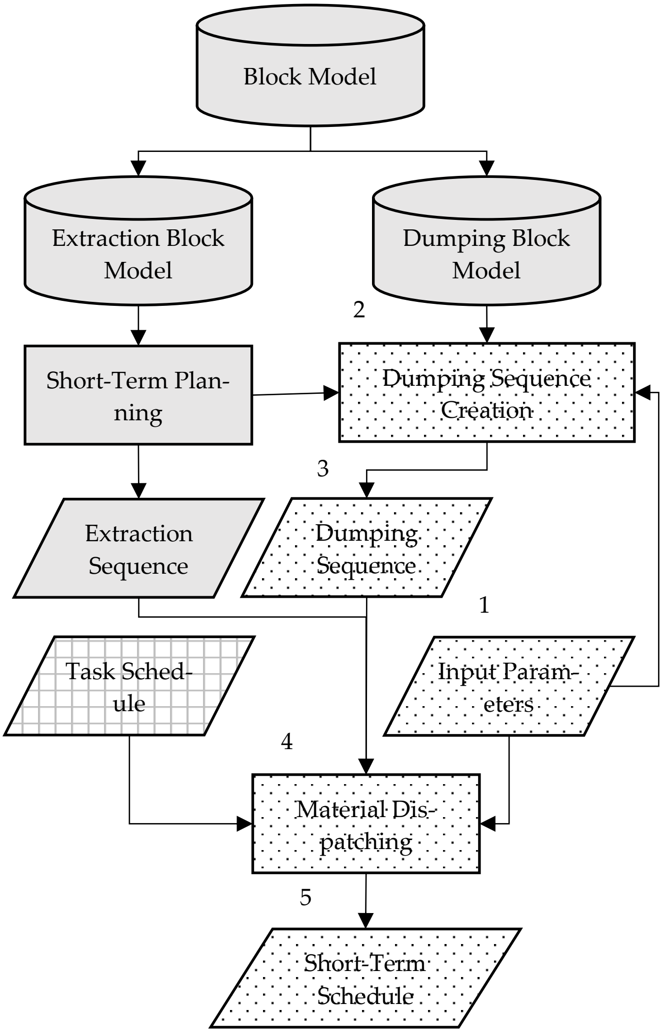

Figure 6.1. Flow diagram of short-term production scheduling in continuous mining systems.

The different ranges of the ratios of the expected amounts of materials at the extraction site to the dumping capacities of the same materials give rise to three different scheduling scenarios. In scenario I, when the extracted to dumped capacity ratio is sufficiently small, the dumping site has sufficient spare capacity to cope with abrupt changes in the extracted materials due to the uncertainty involved. Therefore, in this scenario, challenges are mostly related to the optimization of the dispatch decisions. In scenario II, characterized by an intermediate range of the extracted to dumped capacity ratio, the production capacity may be quite constrained by the dumping capacity when the extraction of different materials spikes at some point in time. In this scenario, even with an optimal dispatch decision, the production for some excavators may fail to reach their targets due to the downtimes. Finally in scenario III, the extracted to dumped capacity ratio is sufficiently large that most of the extracted materials simply cannot be dumped and thus excavators will compete for dumping spaces. In this scenario, dispatch decisions and dumping spaces must be assigned strategically to meet the demands of some excavators in preference to others. In this dissertation, the optimization problem that is under scenario I and II will be addressed. The optimization of short-term scheduling for the case of scenario III involves strategies for the prioritization of excavators. Such strategies, while of considerable interest, are beyond the scope of this study.

To formulate the problem, the following problem context is assumed:

- An opencast mine has multiple extraction benches with only one excavator operating on each bench. Different excavators may have different production capacities and each can extract any type of material. Furthermore, the mine has multiple dumping benches while only one spreader can operate on each bench. Similar to the excavators, different spreaders can have different dumping capacities.
- The units at different benches cannot send material to a same destination at the same time.
- The daily/weekly schedule known as the task schedule is an external input for the short-term scheduling problem. This schedule includes the planned availabilities and downtimes (i.e. planned maintenance) of the equipment.
- Each excavator can supply any spreader and the transportation network is always available. Hence, in the first part of this study, namely optimization, availability of the transportation network is not explicitly considered. Later, in the simulation part, it will be added to the problem as a feedback from the simulator.

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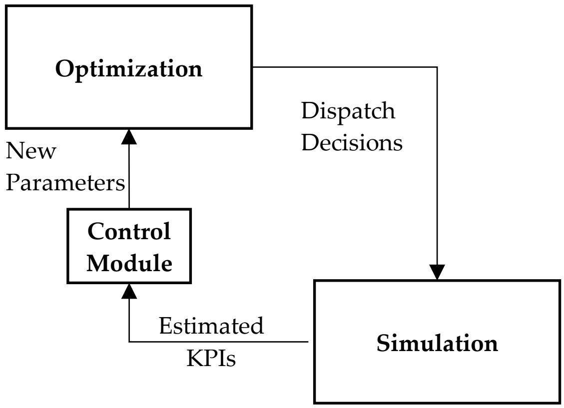
The objective is to minimize downtimes of equipment by effective resource allocations. This will result in decrements in overall costs, including extraction costs, dumping costs, and penalties for deviating from the predefined targets. There are two types of decisions, on the excavator and on the spreader side:

- Decision on the excavator side:
  - Production rate of each excavator (between 0% and 100%)
  - Connection to the spreader
- Decision on the spreader side:

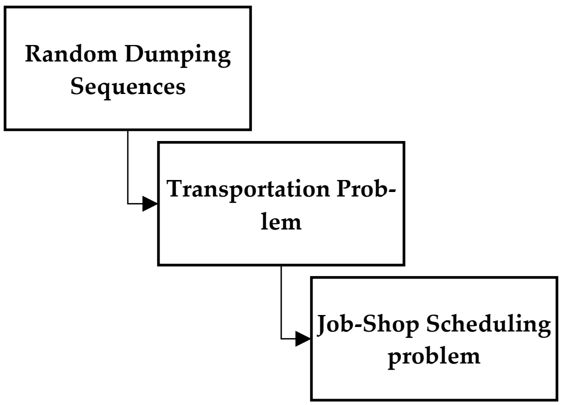
- Dumping sequence (depending on material type available)

6.4. Solution Strategy

To address the above-mentioned problem this dissertation proposes a new simulation-based optimization approach (see Figure 6.2-a) that relies on the use of a deterministic optimization model and a stochastic simulation model. The deterministic model is built using a certain feasible dumping sequence and incorporates a transportation problem and a job-shop scheduling problem (see Figure 6.2-b).



(a) Simulation-based Optimization



(b) Deterministic Optimization Model

Figure 6.2. Configuration of the simulation-based optimization approach.

The transportation problem provides a mechanism to optimize dispatch decisions. In other words, it finds optimal connections between excavators and spreaders. Because of the nature of the transportation problem, it is possible to have multiple connections for an excavator. Therefore, the job-shop scheduling problem deals with the allocation of spreaders to different excavators over time. Its objective is to find the processing sequences and starting times of each operation on each spreader, in order to minimize the total weighted tardiness. A discrete event simulation of the system is executed implementing the dispatch decisions obtained via the deterministic model for a given dumping sequence. The results of multiple simulation replications serve to provide an estimate of a particular performance measure (e.g. utilization). The calculated values are then introduced into a control module. The control module suggests refinements to parameters of the deterministic optimization model (e.g. transportation costs, jobs order, and jobs weight). The iterative process ends after a stopping criterion is met. The strategy uses two aspects of the "Sim-Opt" architecture, which is introduced by (Subramanian et al., 2001).

The following will discuss the three key sub-problems, the creation of a random dumping sequence, the transportation problem, and the job-shop scheduling problem. In the subsequent section, the various computational details that are needed to link these sub-problems and to drive the computations to obtain the desired short-term schedule will be discussed.

6.4.1. Random Dumping Sequences

Schematic representations of different dumping conditions are shown in Figure 6.3. Based on the dumping profile, after building a polder (a 100 *m* section), the possible dumping options are to continue building the polder or dump type 2 material inside the polder, see Figure 6.3-a. If option 2 is randomly selected, the outcome is Figure 6.3-b. Similarly, there are two possible dumping options available in the next stage of dumping. If option 1 is randomly selected, after the first stage, type 2 material can be filled inside the polder, see Figure 6.3-c. After that, there are again two possible dumping options available; to continue building the polder or to dump type 3 material on the top of type 2 material. At this stage, if option 1 is randomly chosen, type 3 material can be dumped inside the polder, Figure 6.3-d. Due to the fixed dumping sequence, here, the only possible dumping option is to continue building the polder with type 1 material.

If the dumping benches with their special profiles are discretized in defined sections (e.g. every 100 *m*), then the evolution of the random dumping sequences over time can be represented by the tree-like structure presented in Figure 6.4. Starting from each node, a large number of possible dumping options at the next dumping stage are expressed as branches stemming from that node. Assuming *m* possible

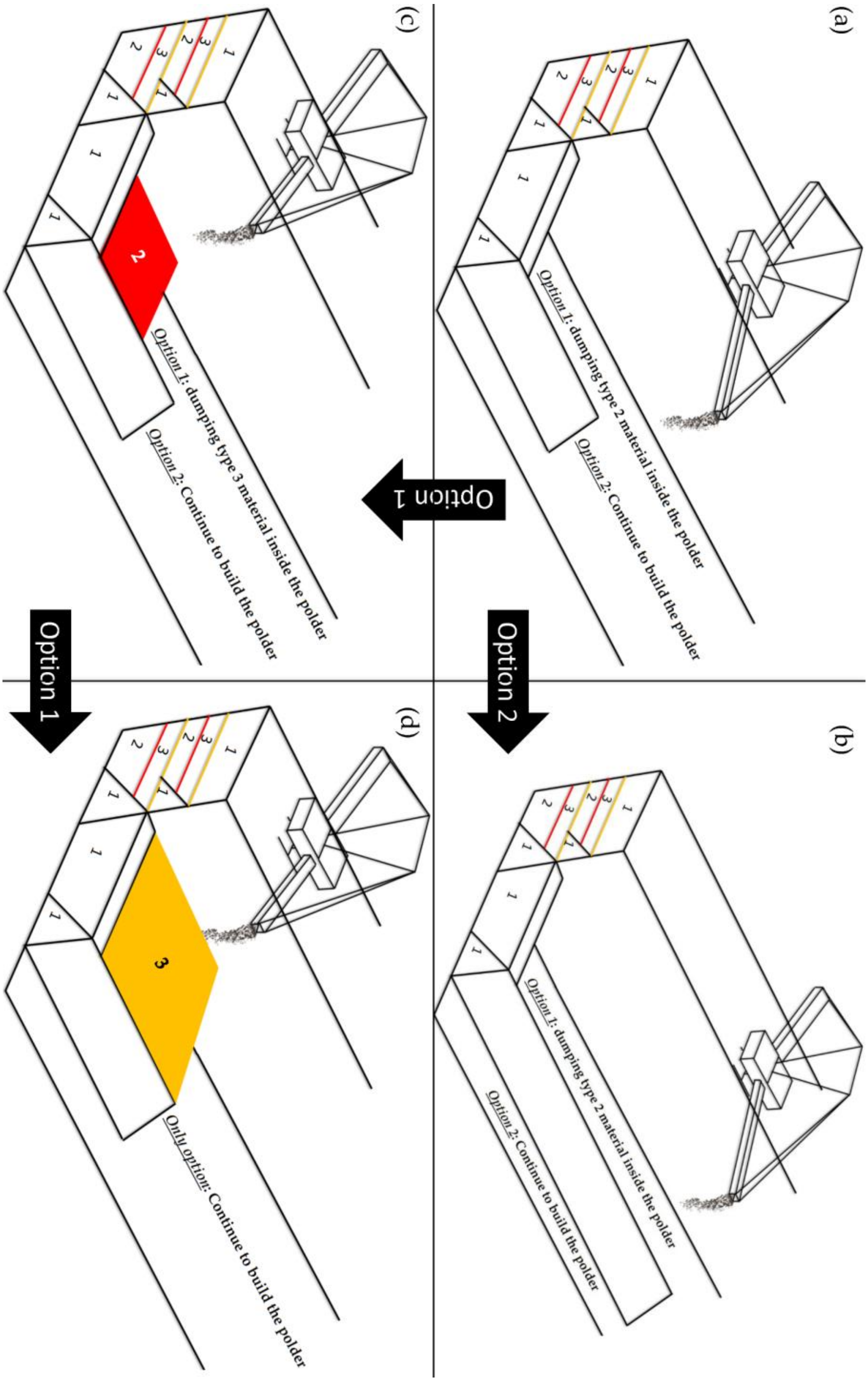


Figure 6.3. Schematic representations of dumping options.

next-stage dumping options at each node, the total number of scenarios will amount to m^S, where S is the total number of dumping stages. Each scenario as a feasible dumping sequence is an input for the transportation problem as is shown in Figure 6.2-b.

6.4.2. Transportation Problem

The transportation problem (TP) is concerned with shipping a commodity between a set of sources (e.g. excavators) and a set of destinations (e.g. spreaders). Each source has a capacity dictating the amount it supplies and each destination has a demand dictating the amount it receives, (Winston and Goldberg, 2004). The TP is a subset of network models and the set of resources and destinations can be illustrated, respectively, by a set nodes. Nodes are connected to each other via arcs; each arc has two major attributes namely the cost of sending unit of a material from one node to the others and the maximum capacity of the arc, see Figure 6.5.

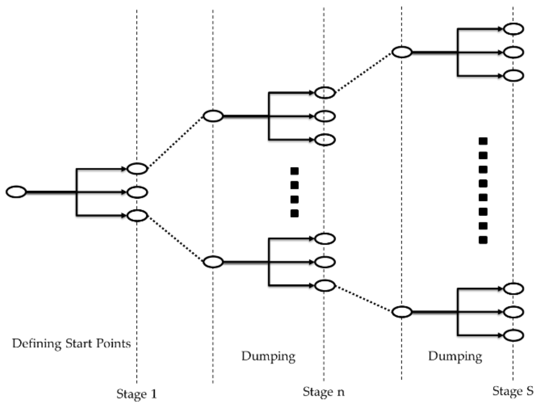


Figure 6.4. Schematic diagram of evolution of random dumping sequences.

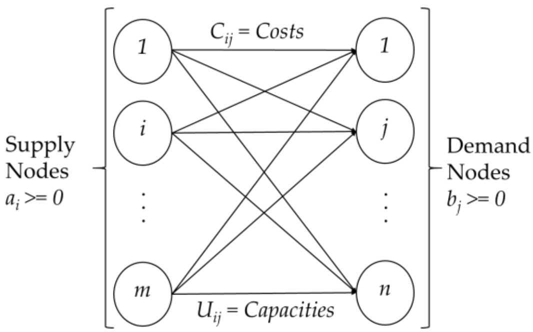


Figure 6.5. A transportation problem with m sources and n destinations.

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An opencast mine extracts material at m different benches ($i = 1, \dots, m$). The amount of material to be extracted at bench i is a_i. The demands for the extracted materials are distributed at n different dumping benches ($j = 1, \dots, n$). The amount of material to be dumped at bench j is b_j. The problem is to find connections between excavators and spreaders at minimum cost. The linear programming (LP) formulation of the problem is as follows, (Winston and Goldberg, 2004):

$Objective\ function$:

$$Minimize\quad z = \sum_{all\ arcs} C_{ij} X_{ij}, \tag{6.1}$$

$s.t.$

$$\sum_{j=1}^{n} X_{ij} \le a_i \qquad for\ i = 1, \dots, m, \tag{6.2}$$

$$\sum_{i=1}^{m} X_{ij} \ge b_j \qquad for\ j = 1, \dots, n, \tag{6.3}$$

$$X_{ij} \ge 0 \qquad for\ all\ i\ and\ j, \tag{6.4}$$

where, X_{ij} is the number of units of material sent from node i to node j through arc *(i, j)*; C_{ij} is the cost of transporting one unit of material from node i to node j via arc *(i, j)*. The objective function, denoted by Eq. (6.1) involves a deterministic optimization in which the total cost of sending materials from supply points to demand points is minimized. In constraint (6.2), the sum of all shipments from a source cannot exceed the available supply. Constraint (6.3) specifies that the sum of all shipments to a destination must be at least as large as the demand. Constraint (6.4) is a binding constraint.

Consider the feasibility of the problem. The only way that the problem can be feasible is if total supply exceeds total demand ($\sum_{i=1}^{m} a_i \ge \sum_{j=1}^{n} b_j$). Two conditions can be implied from this:

- When the total supply is equal to the total demand (i.e. $\sum_{i=1}^{m} a_i = \sum_{j=1}^{n} b_j$) then the transportation model is said to be balanced.

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- A transportation problem in which the total supply and total demand are unequal is called unbalanced. If there is excess demand, a dummy source is introduced (i.e. a fictitious bench). The amount shipped from this dummy source to a destination represents the shortage quantity at that destination. If there is excess supply, a dummy destination is added to the network. Likewise, the amount received from this dummy destination from a source represents the excess quantity at that source.

Due to the nature of the transportation problem, it is possible that an excavator has to send materials to multiple spreaders. The next section will discuss the job-shop scheduling problem, which deals with the allocation of spreaders to different excavators over the time.

6.4.3. Job-Shop Scheduling Problem

The job-shop scheduling problem (JSP) consists of a finite set of jobs $J = \{1, \dots, n\}$ and a finite set of machines $M = \{1, \dots, m\}$. In this dissertation, excavators are defined as jobs and spreaders are defined as machines. The aim is to find a schedule of J on M under the conditions mentioned below:

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- For each job $j \in J$, a list $(O_1^j, \dots, O_h^j, \dots, O_m^j)$ of the machines which represents the processing order of j through the machines is given. Note that O_h^j is called the *h-th* operation of job j and O_m^j is the last operation of job j.
- The processing order for each job is fixed, thus, a machine-sequencing problem for every job should be taken into account.
- For every job j and machine i, a non-negative P_{ij} is given, which represents the processing time of j on i.
- Each machine must always be available and can process at most one job at a time, and once a job starts on a given machine, preemption is not allowed.
- Every job j has an assigned release time $r_j \geq 0$ so that the first operation cannot start before r_j. In this dissertation, r_j is given in the task schedule.
- An additional attribute of a job j is its weight w_j, which represents the relative importance of j in comparison to other jobs.
- Furthermore, every job j has a due date $r_j \geq 0$ which should, but does not necessarily have to, be met in a schedule.

In this study, the objective is to minimize the obtained total weighted tardiness, as defined $TWT = \sum_{j=1}^{n} w_j \cdot t_j$, where $t_j = \max\{0, c_j - d_j\}$ is the resulting tardiness of job j in a schedule, d_j is the due date of the job, and c_j is its completion time. From now on, this problem is referred to as JSPTWT. Ku and Beck (2016) investigated the size of problem that can be solved by of Mixed Integer Programming (MIP) formulation. For a moderately sized problem up to 10 jobs and 10 machines, with the recent technology, MIP finds the optimum solution in a very reasonable amount of time. They also compared the performance of the four MIP models for the classical JSP. They concluded that the disjunctive MIP formulation with the use of the GUROBI v6.0.4 solver (Gurobi Optimization, 2016) gives the fastest result for a moderate sized problem. The list below is the disjunctive MIP formulation of JSPTWT, based on Manne (1960)'s formulations. The decision variables are defined as follows:

- X_{ij} is the integer start time of job j on machine i
- Z_{ijk} is equal to 1 if job j precedes job k on machine i

$Objective\ function$:

$$Minimize \sum_{j=1}^{n} w_j \cdot t_j \tag{6.5}$$

$s.t.$

$$X_{\sigma_h^j, j} \geq X_{\sigma_{h-1}^j, j} + P_{\sigma_{h-1}^j, j}, \qquad \forall j \in J,\ h = 2, \ \dots, m, \tag{6.6}$$

$$X_{ij} \geq X_{ik} + P_{ik} - V \cdot Z_{ijk}, \qquad \forall j, k \in J,\ j < k,\ i \in M, \tag{6.7}$$

$$X_{ik} \geq X_{ij} + P_{ij} - V \cdot (1 - Z_{ijk}), \qquad \forall j, k \in J,\ j < k,\ i \in M, \tag{6.8}$$

$$t_j \geq X_{mj} + P_{mj} - d_j, \qquad \forall j \in J, \tag{6.9}$$

$$t_j \geq 0, \qquad \forall j \in J, \tag{6.10}$$

$$X_{1j} \geq r_j, \qquad \forall j \in J. \tag{6.11}$$

Constraint (6.6) is the precedence constraint. It ensures that all operations of a job are executed in the given order. The disjunctive constraints (6.7) and (6.8) ensure that no two jobs can be scheduled on the same machine at the same time. V has to be assigned to a large enough value to ensure the correctness of (6.7) and (6.8). In this dissertation, it is defined as $V = \sum_{j \in J} \sum_{i \in M} P_{ij}$, since the completion time of any operation cannot exceed the summation of the processing times from all the operations. Constraint (6.9) and (6.10) measure the resulting tardiness of each job. Finally, constraint (6.11) ensures that a job cannot start before its release time, and thus, captures the non-negativity of the decision variables X_{ij}.

As an example, Figure 6.6 shows a simple JSP in which three jobs J1, J2, and J3 are to be scheduled on three machines M1, M2, and M3. The graph on the top represents the precedence constraints. The Gantt chart on the bottom displays a feasible schedule that satisfies the precedence constraints (Ku and Beck, 2016). As can be seen, the makespan is the total length of the schedule (that is, when all the jobs have finished processing). The term makespan will frequently be used in the case study section. The next section will elaborate more on the computational framework of the connection of the sub-problems.

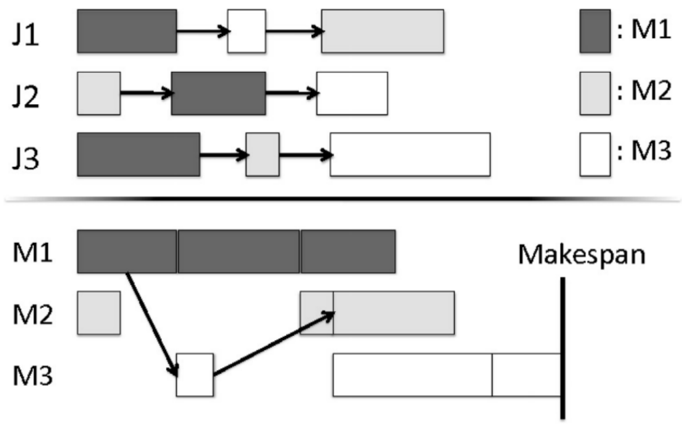

Figure 6.6. A simple job-shop scheduling problem, (Ku and Beck, 2016).

6.5. Computational Framework

In this section, the overall computational approach is described. First, input parameters are explained. Then, the computational logic with the details of the integration of the sub-problems together and with the discrete event simulation is discussed. After that, the simulation based optimization framework is presented.

6.5.1. Input Parameters

The second step of the optimization of short-term scheduling starts with the assignment of input parameters. The definitions and their functionalities are as follows:

- Start points of dumping in different benches, i.e. the start locations of spreaders on benches at the beginning of the working shift. This is an input for the creation of random dumping sequences.
- The allowed range of movement for spreaders, i.e. in what range it is allowed to transport spreaders and start a new dumping profile. This is also an input for the creation of random dumping sequences.
- Transportation costs, these costs are used to distinguish between different destinations for a source in the transportation problem.
- Machine sequencing, the Earliest Due Date (EDD) sequencing method is used to create processing orders of the jobs in the JSP.
- Finally, Job weights are some other input parameters for the JSPTWT. For instance, they can be used to prioritize an excavator if a bottleneck is seen after the simulation.

The aim is to find the best combination of these parameters using a simulation based optimization approach to achieve the optimum short-term schedule.

6.5.2. Deterministic Optimization with Embedded Simulation

The following describes the details of the integration of the sub-problems together and to the discrete event simulation in walk-through steps.

Step 1: start with an arbitrary set of input parameters.
Step 2: create a sufficient number of random dumping sequences, $\{1, \dots, R_s\}$.
Step 3: for a certain dumping sequence, $d = 1, d \in R_s$, optimal connections can be found using the transportation problem.

Step 3.1: check the availability of the equipment based on the given task schedule and create the nodes.
Step 3.2: start with first blocks in the given extraction sequence and assign their volumes as a_i to supply nodes in the TP formulation.
Step 3.3: assign the volumes of the first sequence of blocks in the given dumping sequence as b_i to demand nodes in the TP formulation.
Step 3.4: check if problem is balanced, if not add dummy nodes to the network.
Step 3.5: create arcs between supply and demand nodes. Only these nodes get connected that have the same type of material.
Step 3.6: add a capacity to the arcs. In the TP, the capacity is set to be infinite for all the arcs.
Step 3.7: add costs to the arcs. In an opencast mine, the potential costs can be:

- Excavators and spreaders on the same level (altitude) get lower cost of transportation.

- Length of belt conveyors between supply nodes and demand nodes; the closer the equipment the lower the costs.
- Difference between the production capacity and dumping capacity of the equipment; the lower the difference the lower the costs.

Step 3.8: build the LP model with the help of Eqs. (6.1)–(6.4) and solve it by the GUROBI solver.

Step 3.9: calculate the residual volumes and add them to the next iteration of the optimization.

Step 3.10: go to step 3.1 and repeat steps 3.1–3.10 until all the blocks are extracted in the given extraction sequence.

Step 3.11: check for feasibility of the schedule, if there is residual volume left on the extraction side, set $d = d + 1$ and go to step 3 until $d = R_s$.

Otherwise, continue.

Step 4: create the input for the JSPTWT and build the MIP model using Eqs. (6.5)–(6.11) and solve it with the GUROBI solver.

Step 5: create the Gantt chart. The output of the JSPTWT is the optimum short-term schedule for the given extraction and dumping sequence (d).

Step 6: run the discrete event simulation for the given short-term schedule.

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Step 7: record the state (utilizations, amounts) at the end of the time horizon.

Step 8: set $d = d + 1$ and go to step 3 until $d = R_s$.

6.5.3. Simulation Based Optimization Framework

A more detailed flow diagram, which summarizes the overall computational framework, is presented in Figure 6.7. It combines the deterministic optimization with the stochastic simulation in a closed loop. Most of the steps are explained in detail in the previous section. As can be seen, the simulation is implicitly built over the embedded optimization. Once the computations over the simulation loop are completed, a number of best schedules based on the user-defined targets such as shorter makespan, higher utilization of equipment are selected. These are analyzed in the control modules; if the stopping criteria are met, the algorithm stops; otherwise, a new set of input parameters is introduced to the optimizer. The following section presents more details about the interactions between the components in a simulation-optimization platform.

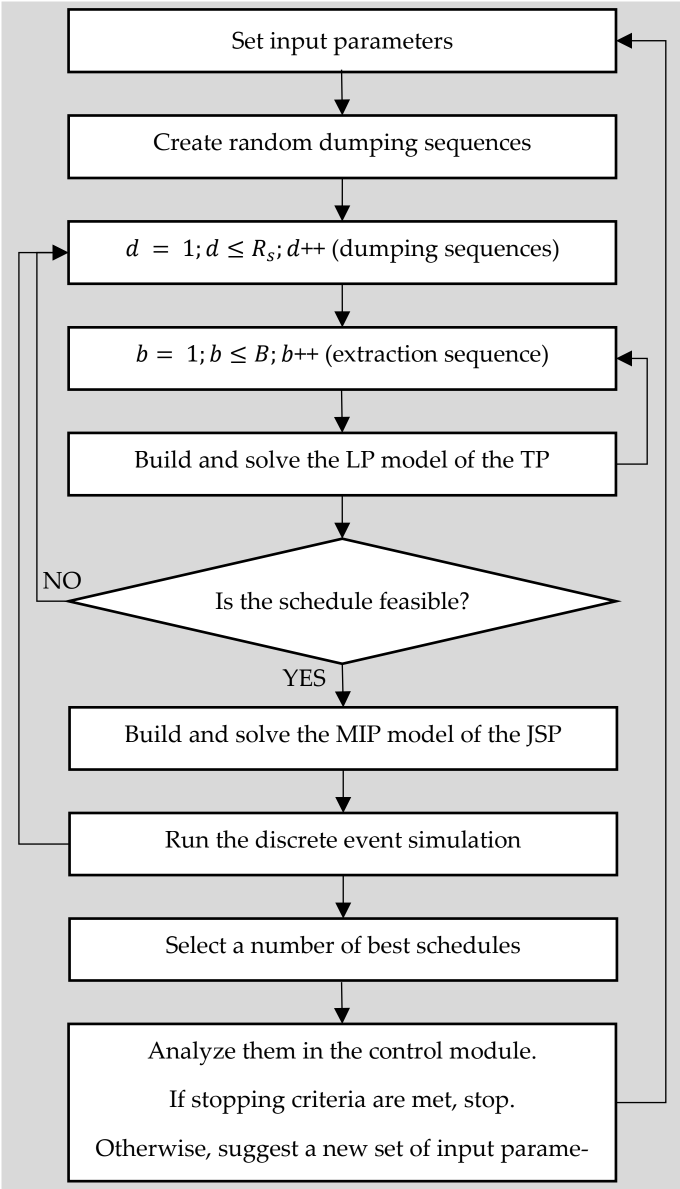

Figure 6.7. Computational flow diagram.

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6.6. Implementation of the Computational Framework

The implementation of the proposed simulation-based optimization approach consists of the following major components: the computational control module, the databases, the three modules for the creation of random dumping sequences, the transportation problem and the job-shop scheduling problem, the discrete event simulation with its interface, the post-processing module, and finally the control module, Figure 6.8. The computational control module is responsible for controlling interactions of computational components. It has various functions including:

- Issuing commands for retrieving information from the database.
- Generating/updating and releasing commands for executing the steps of the algorithm.
- Re-processing and controlling the output of each computational component before issuing the next command.
- Selecting a number of best schedules based on the defined criteria to proceed the algorithm to the simulation part.

The database contains information about the geological block model, the given extraction sequences, and the task schedule. These data are stored in a spreadsheet file. Since the computational control module is coded in Python, a publicly available Pandas library (McKinney, 2010) is used to access each cell in the spreadsheets. Big datasets can be readily read and stored in DataFrames with the help of Pandas library.

The three major components of the deterministic optimization procedure were explained in detail in the previous sections. It should be noted that to solve the LP or the MIP models, the GUROBI Python interface is used. After the selection of a number of best schedules by the computational control module, the data are recorded in two separate databases, namely, the block model and the schedule. These two are the major inputs for the discrete event simulation of an opencast mine.

The discrete event simulation model is built in Arena® simulation environment. The detail of the construction of the simulation model of an opencast mine can be found in the previous chapters. A process worth attention is the simulation model interface, which is situated between the computational control module and the simulator. This process is required because there is no direct way to interact with the simulator using, for instance, the command line. Instead, the program relies on automation via Visual Basic for Applications (VBA), a Microsoft technology for creating interconnection between applications. This technology is not available in Python, thus the simulation model interface is written in Visual Basic and compiled as an executable that can be controlled and run with the relevant parameters. When the simulation run is completed, the VB script releases a command to the controller.

The post-processing module processes the simulation outputs and creates plots and tables. Finally, the control module calculates the differences between the current results with the predefined targets. If another loop of simulation-optimization is required, new input parameters are suggested to the computational control module.

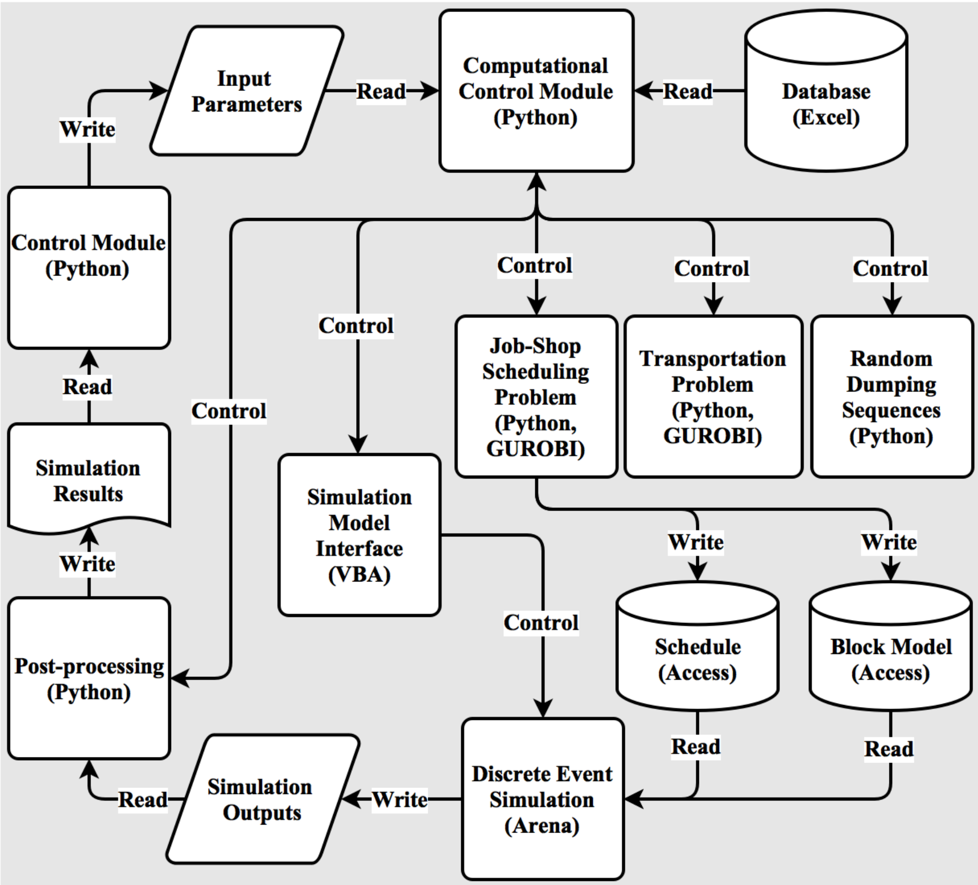

Figure 6.8. Simulation-optimization platform.

6.7. EXPERIMENTAL INPUT DATA

The following presents the input data used for this case study. Table 6.1 gives the extraction sequences of different material types as an input. These will be used as a guide in the creation of random dumping sequences. In total, over 830 thousands m^3 of different material types should be scheduled to be extracted. The amounts of different material types for each sequence are shown in the table.

Table 6.1. Extraction sequences as an input.

Extraction Sequence	Material Types				
	M2T (m³)	Coal (T)	M2N (m³)	M1 (m³)	Total (m³)
1	9,001	3,621	1,215	5,983	19,648
2	4,573	2,008	-	15,486	21,971
3	4,845	3,621	1,090	17,505	26,889
4	10,093	2,008	8,642	22,805	43,452
5	16,989	3,621	-	28,089	48,527
6	14,343	2,008	-	28,385	44,640
7	13,984	6,613	12,832	26,089	59,203
8	22,732	11,520	18,346	12,769	64,818
9	21,368	6,613	-	28,316	55,982
10	-	11,520	25,313	33,264	69,548
11	15,166	6,613	10,944	25,642	58,050
12	21,115	11,520	8,949	19,189	60,224
13	19,732	6,583	-	37,663	63,665
14	-	7,742	9,721	35,246	52,340
15	7,991	6,583	13,593	15,143	42,997
16	-	7,742	-	31,333	38,706
17	-	6,583	9,721	11,979	27,970
18	-	7,742	-	16,075	23,448
19	-	12,115	-	-	11,538
Total	181,932	126,376	120,366	410,961	833,617

As discussed earlier, the extraction sequence of material ignores operational considerations and equipment availability. The availably of the equipment (the task schedule in Figure 6.1) as another external input is given in Table 6.2. The number "0" denotes that the equipment is unavailable and "1" vice versa. A closer look at the task schedule reveals that excavators S1, B7, and spreader I7 are unavailable, and thus the transportation problem will have six supply nodes and seven demand nodes. The maximum allowed ranges of movement for different spreaders are presented in Table 6.3. They are important parameters for the creation of the random dumping sequences. Here, their range is defined as ± (200 – 500) meters for all spreaders. During the simulation-optimization loop iterations, the optimum value will be determined. The plus-minus sign indicates that the spreader has the option to choose a dumping location from the front or back side of its standing position. Other important input parameters are the job weights for the job-shop scheduling problem. With the help of these parameters, different excavators can be prioritized against each other. For example, if two excavators have to send extracted materials to one spreader, the one whose job weight is higher will be scheduled first. In this case, job weights are considered to be the same for all excavators, see Table 6.4.

Table 6.2. Task schedule of BWEs and spreaders.

Bench	First Shift	Second Shift	Third Shift
S1	0	0	0
B1	1	1	1
B2	1	1	1
B3	1	1	1
B4	1	1	1
B5	1	1	1
B6	1	1	1
B7	0	0	0
I1	1	1	1
I2	1	1	1
I3	1	1	1
I4	1	1	1
I5	1	1	1
I6	1	1	1
I7	0	0	0

Table 6.3. Maximum and minimum allowed range of movements for the spreaders.

	Benches						
	I1	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**
Range of allowed movement	±(200 – 500)	±(200 – 500)	±(200 – 500)	±(200 – 500)	±(200 – 500)	±(200 – 500)	±(200 – 500)

Table 6.4. The job weights which are used in the job-shop scheduling problem.

	Benches							
	S1	**B1**	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**
Job weights	1	1	1	1	1	1	1	1

The defined costs for the transportation problem are as follows:

- Distance to the destination: This cost can be calculated by Eq. (6.12). Here, C_1 is the associated cost coefficient, distance (m) is the length of the belt conveyors between the source and the destination and $Speed_{belt}$ $\left(\frac{m}{s}\right)$ is the speed of the belt conveyors. It can be interpreted as the amount of time that is needed to transport one m^3 of any material from the supply point to the demand point. The closer the equipment, the lower the cost.

$$Cost_{Distance}\,(min) = C_1\left(\frac{Distance(source, destination) * 60}{Speed_{belt}}\right) \tag{6.12}$$

- Capacity difference: This cost can be calculated by Eq. (6.13). Here, C_2 is the associated cost coefficient, inflow (m^3) is the amount of material to be sent to the destination from the source. $Capacity_{source}$ and $Capacity_{destination}$ $(\frac{m^3}{h})$ are the theoretical capacities of the supply point and demand point, respectively. It can be interpreted as a penalty for connecting a small excavator to a big spreader or vice versa. Altogether, the calculated value is the amount of extra time that is needed to extract or dump the material.

$$Cost_{Capacity}\,(min) = C_2\left(\left(\frac{Inflow(source, destination)}{|Capacity_{source} - Capacity_{destination}|}\right) * 60\right) \tag{6.13}$$

- Altitude difference: This cost can be calculated via Eq. 6.14. Here, C_3 is the associated cost coefficient. For clarification, Figure 6.9 is used to describe the parameters of this equation. In summary, it measures amount of the extra transportation time that is needed if the supply point and the demand point are not at the same level. As can be seen in Figure 6.9, it is assumed that the maximum angle of inclination of the belt conveyors is 20 degrees. Here, $elev.(BWE)$ and $elev.(SP)$ are the elevations of excavators and spreaders, respectively.

$$Cost_{Altitude}\,(min) = C_3\left(\begin{array}{c}\left(\dfrac{|elev.(BWE) - elev.(SP)|}{sin\,20°}\right) - \\ \left(\dfrac{|elev.(BWE) - elev.(SP)|}{tan\,20°}\right)\end{array}\right)\left(\frac{60}{Speed_{belt}}\right) \tag{6.14}$$

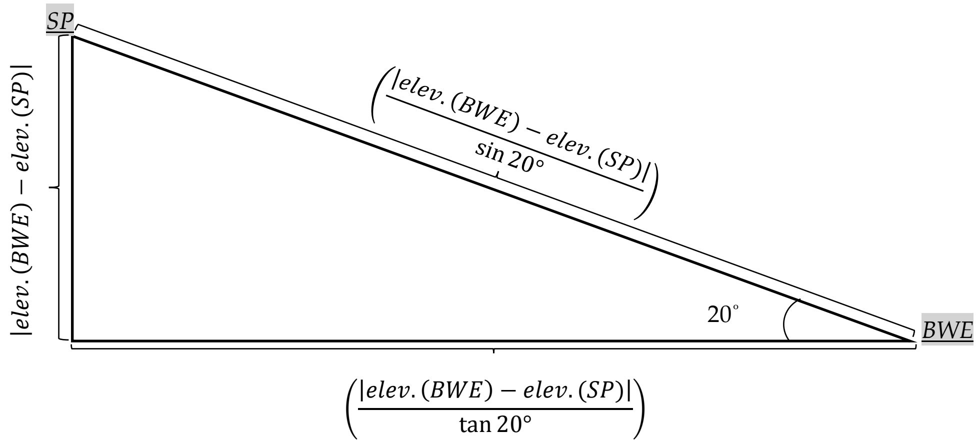

Figure 6.9. A schematic illustration of the parameters of Eq. (6.14).

The level of the importance of the different costs is determined by cost coefficients (i.e. C_1, C_2, and C_3). The variation ranges of the cost coefficients are given in Table 6.5. In this case, their variation range is defined to be from zero to three for all arcs in the transportation problem. Zero means that the related cost has no influence on the solution of the transportation problem; on the contrary, three means the related cost has the maximum possible influence on the solution of the transportation problem. The following section presents and discusses the obtained results.

Table 6.5. Different cost coefficients used in the transportation problem.

	Cost Coefficients		
	Distance to destination C_1	Capacity difference C_2	Altitude difference C_3
Variation ranges	0 – 3	0 – 3	0 – 3

6.8. Results and Discussion

The case problem was solved with the proposed simulation-optimization approach. The extracted to dumped capacity ratio is set to be sufficiently small (scenario I) thus the dumping site has sufficient spare capacity. For each loop iteration, one hundred random dumping sequences with a slice (section) length of 100 m are set to be created. The number of simulation replications is set to 20 replications as is suggested in Section 4.1.6. The computation for the complete case was run on a

Core™ i5-3380M Intel CPU @ 2.90GHz and each loop iteration took about seven minutes.

Figure 6.10 illustrates the trajectory of the number of feasible short-term schedules as the simulation-optimization loop iterations progressed. In the 1st loop iteration, no feasible schedules were seen. After that, the control module suggested a new set of input parameters. Here is the beginning of an upward trend. From the 2nd to the 7th loop iteration, the number of feasible schedules increased gradually, but rose sharply in the 8th loop iteration. It reached the highest point, with a figure of 76 feasible schedules, in the 9th loop iteration. There was a slight drop in the last loop iteration when the stopping criteria were met.

Box plots are drawn for makespan values of the feasible short-term schedules, see Figure 6.11. They provide a useful way to visualize the range, overall patterns, and also to study the distributional characteristics of a group of makespans as well as the level of the makespans. A single striking observation about the box plots could be a downward trend of the minimum values as the simulation-optimization loop proceeds. This indicates that the quality of solutions increases, with a figure of 24%, until it reaches its optimum value in the 10th loop iteration.

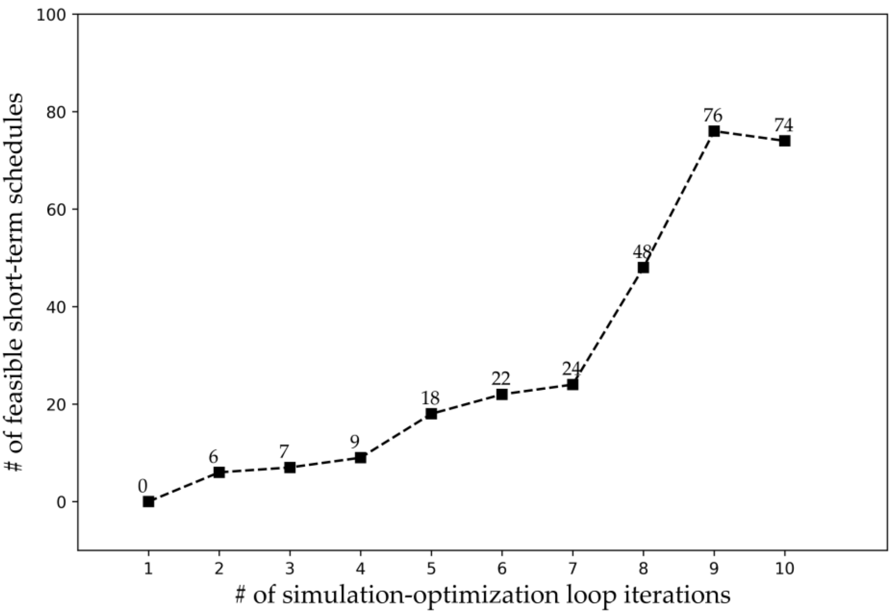

Figure 6.10. Trajectory of feasible short-term schedules as simulation-optimization loop proceeds.

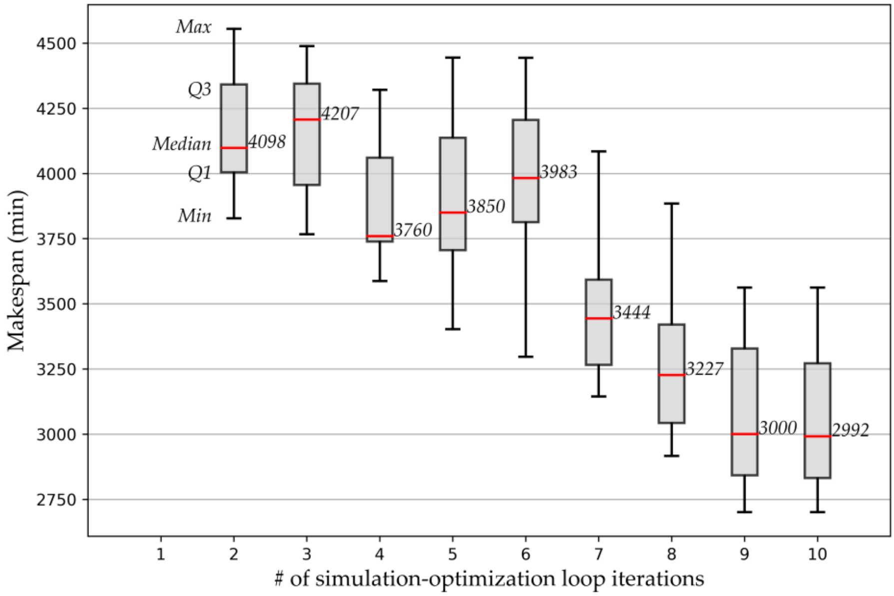

Figure 6.11. Box plots of makespan values of the feasible short-term schedules for different simulation-optimization loop iterations.

6

Some observations emerge from the box plots:

- The box plots of the 5th and the 6th loop iterations are comparatively tall. This suggests that the range of makespan values are quite disperse. The possible explanation for this could be that the algorithm starts to explore a wider range in the solution space of this problem.
- In almost all the box plots, the 4 sections (quartiles) of the box plot are uneven in size. This shows the diversity, in the thicker section, and the similarity, in the thinner section, of the obtained results.
- The medians of the box plots of the 9th and the 10th loop iterations are at the same level, however they show a different distributional characteristic.
- Most of the box plots are positively (right) skewed and only two of them show a symmetric distribution (7th and 8th).

To reduce the computational load, in every simulation-optimization loop iteration, the ten best schedules are selected to be tested by the simulator and only their outputs are analyzed by the control module to redefine the input parameters. The criteria for the selection of the best schedules are:

- Makespan: Having a short makespan is a necessary condition for the selection of the best schedules but it is not sufficient. The following two criteria should also be considered.
- Utilizations of excavators: After the makespan, the total and also individual utilizations of the excavators should be analyzed in order to select the best schedules. For example, Figure 6.12 presents the utilizations of nine different schedules ((a) – (i)) whose makespan are about 2700 (*min*). The total utilizations of the equipment vary from 62% – 67%. Among these, schedules (b), (e), (f), and (i) have the highest utilizations and are added to the selection list. Next, the other criterion should be taken into account to narrow down the list.

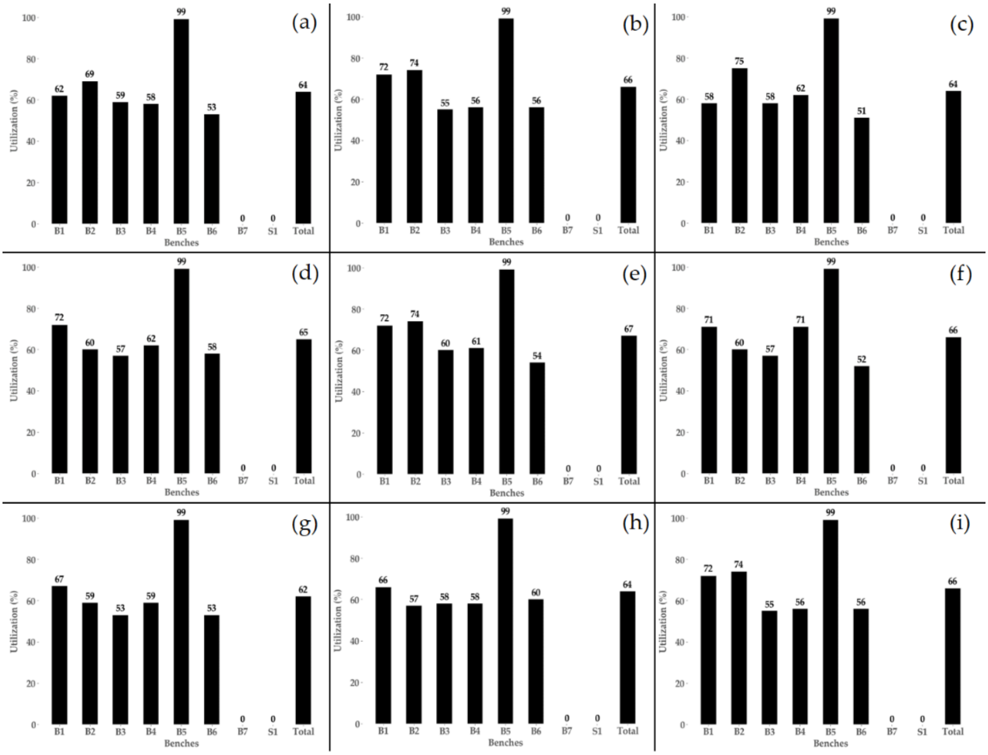

Figure 6.12. Utilizations of nine different feasible schedules, output of optimization block.

- Utilizations of Spreaders: Likewise to the excavators, the total and individual utilizations of the spreaders should be analyzed. Figure 6.13 displays the utilization of the same nine schedules ((a) – (i)). Based on the selection list's items ((b), (e), (f), and (i)), the total utilizations fluctuate between 48% – 49%. Here, the individual utilizations play a crucial role. For instance, consider schedule (f) of Figure 6.13, the utilization of *I2* is about 97% while other spreaders have lower utilizations. In this case, experiments revealed that there is a high chance of not meeting the target utilization when the unscheduled breakdown behavior is added to the model by the simulator. The argument can be correct for schedule (g) as well; its total utilization is about 51%, but there is a high chance to not to meet the target in reality. These investigations narrow down the list to the schedule (e) in Figure 6.13 to be the best schedule. Having defined the best schedule, the following will now move on to discuss more details of its results.

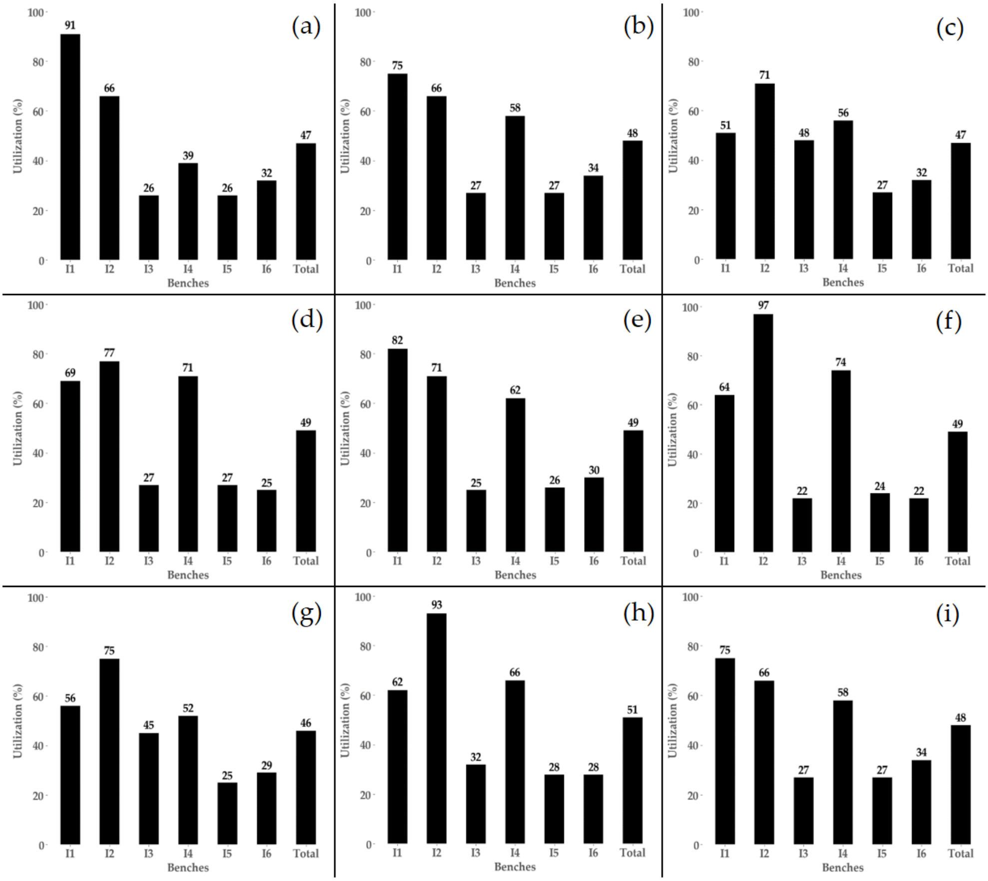

Figure 6.13. Utilizations of nine different feasible schedules, output of optimization block.

The output result of the transportation problem is given in Table 6.6. For each extraction sequence, the transportation problem finds the optimal connections between the excavators and the spreaders. For instance, in the first extraction sequence, bench *I1* will receive materials from extraction benches *B4* and *B1*. The question is now, "which one of the excavators sends the materials first?" The job-shop scheduling problem will find the optimal schedule over time. Its detail and the formulation were discussed earlier in Section 5.3. The output of the job-shop scheduling problem in the form of a Gantt chart is presented in Figure 6.14. The completion times (c_i) and start/end times of different tasks of benches are shown in the figure. As can be seen, bench *B4* sends first, then bench *B1*. Waiting for the assigned spreader causes the gap between two tandem tasks. In the case of bench *B5*, which produces only coal, no waiting times were expected as a result of material changes. In summary, the proposed method minimizes the number of these gaps with effective resource allocations.

The details of the simulation model of the Hambach mine from the simulation concept to practical full-scale implementation can be found in Chapter 5. The following will conclude the salient findings of this study.

Table 6.6. Output of the transportation problem.

Extraction Sequence	Connections of the Spreaders to Excavators
1	(I1 => B4), (I1 => B1), (I2 => B3), (C => B5), (I2 => B6), (I3 => B2)
2	(I1 => B3), (I1 => B1), (I2 => B2), (C => B5), (I2 => B6), (I1 => B4)
3	(I1 => B4), (I2 => B3), (I1 => B1), (I5 => B6), (C => B5), (I2 => B6), (I3 => B2)
4	(I1 => B1), (I4 => B4), (I2 => B3), (I4 => B6), (C => B5), (I3 => B2)
5	(I2 => B3), (I2 => B6), (I1 => B4), (I4 => B1), (C => B5)
6	(I2 => B2), (I1 => B3), (I1 => B1), (I4 => B4), (C => B5), (I2 => B6), (I1 => B4)
7	(I2 => B2), (I1 => B3), (I4 => B4), (I4 => B6), (C => B5), (I2 => B1)
8	(I6 => B2), (I1 => B1), (I2 => B3), (C => B5), (I5 => B4), (I2 => B6)
9	(I6 => B2), (I1 => B1), (I4 => B4), (C => B5), (I2 => B6), (I3 => B2), (I4 => B1)
10	(I6 => B2), (I4 => B4), (I2 => B3), (C => B5), (I5 => B4), (I2 => B6), (I1 => B4), (I4 => B1)
11	(I2 => B2), (I1 => B3), (I1 => B1), (I4 => B4), (I4 => B6), (C => B5)
12	(I1 => B1), (I5 => B2), (C => B5), (I5 => B3), (I1 => B4), (I2 => B6)
13	(I6 => B2), (I4 => B4), (I3 => B6), (I3 => B1), (C => B5), (I3 => B3), (I1 => B4)
14	(I6 => B2), (I1 => B1), (I2 => B3), (C => B5), (I3 => B3), (I1 => B4), (I1 => B6)
15	(I5 => B6), (I2 => B3), (C => B5), (I4 => B4), (I3 => B6)
16	(I4 => B4), (I2 => B6), (I6 => B3), (I6 => B6), (C => B5)
17	(I4 => B3), (C => B5), (I4 => B4), (I1 => B4)
18	(I1 => B4), (I1 => B6), (I1 => B3), (C => B5)
19	(I5 => B6), (I5 => B3), (C => B5), (I4 => B4), (I3 => B6)

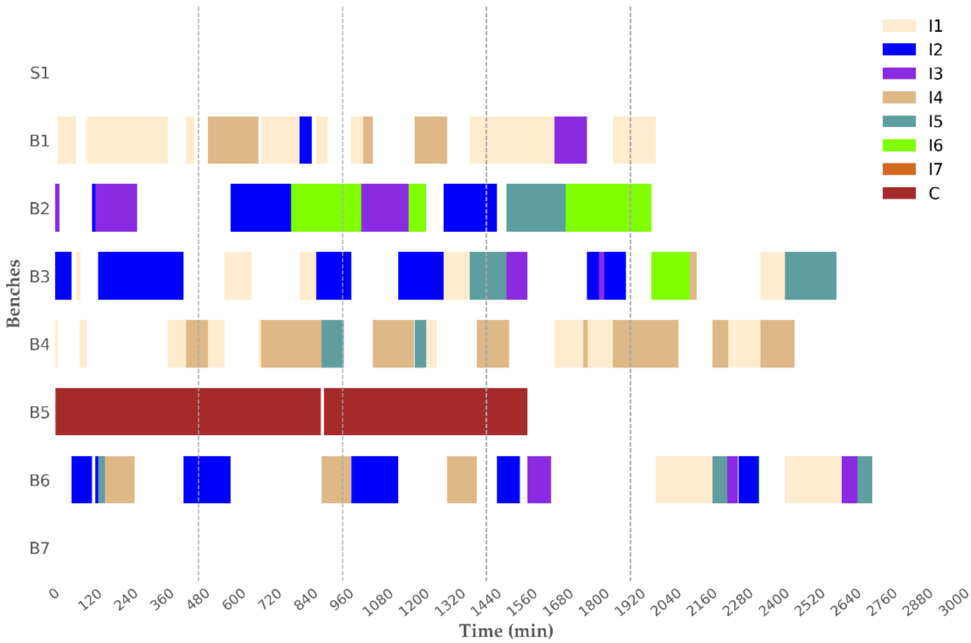

Figure 6.14. A feasible Gantt chart.

6.9. Conclusions

Throughout this chapter, a new simulation-based optimization approach has been proposed. The approach was capable of optimizing the dispatch decisions in an opencast mine operated under the paradigm of continuously excavated material flow. It combined deterministic optimization with stochastic simulation in a closed loop. A transportation problem and a job-shop scheduling problem composed the optimization model. The performance of the proposed approach was tested in the Hambach mine (case 2). In this case, for a given extraction sequence, one hundred random dumping sequences were created. From the obtained results, it can be concluded that:

- The number of feasible short-term schedules increased as the simulation-optimization loop progressed.
- The algorithm stopped after ten loop iterations when no further improvements were seen.

- The box plots of the makespans of the schedules showed a downward trend of the minimum values as the simulation-optimization loop proceeded. This indicated that the quality of solutions increased, with a figure of 24%, until it reached its optimum value in the 10^{th} iteration.
- The selection of the ten best schedules to be run in the simulator reduced the computational load quite effectively. The criteria for the selection of the best schedules were the makespans, total/individual utilizations of excavators, and total/individual utilizations of spreaders.

7

Conclusions & Future Perspectives

7.1. Conclusions

This chapter, first, provides general conclusions from this dissertation and then outlines recommendations for future research. Continuous mining systems require large investments and operational costs. Decisions in daily production scheduling are impacted by uncertainties, such as incomplete knowledge about the deposit and operational downtimes. These can have a significant influence on the actual production performance. In this dissertation, a stochastic mine process simulator capable of capturing different sources of uncertainty, including geological uncertainty and unscheduled breakdowns of equipment, has been developed. An algorithmic approach to simulate the process of opencast mines was proposed. The evaluation function and three major KPIs including coal quality, quantity, and utilization of major equipment were defined. The approach was framed in a formal description containing all mining elements. Throughout this study, two types of simulations, namely Monte-Carlo simulation and Discrete-Event Simulation (DES), were integrated. A synthetic experiment was used to demonstrate the strength and limitation of the integrated approach; TRL 4 was achieved. Thereafter, it has been extended to a new technology readiness level (TRL 6) by implementing it in an industrial relevant environment. The obtained results showed that such an approach provides the mine-planning engineer a valuable tool to foresee critical situations affecting the continuous supply of raw material to customers, and the system performance. This dissertation further proposed a new simulation-based optimization algorithm applicable to short-term production planning of opencast mines. Deterministic optimization and stochastic simulation were combined in a closed loop. The proposed approach was capable of optimizing dispatch decisions for the given extraction sequences. Furthermore, in this dissertation, in order to overcome the capacity constraint problem at the dumping site, the creation of a number of random dumping sequences was proposed. The following sub-sections contain chapter-specific conclusions.

7

Chapter 4: Synthetic Experiment: 2D Case Study

A synthetic experiment in a fully controllable environment demonstrated that the developed concept was capable of quantifying the effects of geological uncertainty and unscheduled downtimes. Their impacts on the ability of delivering contractually defined coal quantities and qualities have been shown. It has been found that:

- Relying on the estimated model would indicate a biased and optimistic prediction of the ash content. This is due to ignoring the in-situ variability and the geological uncertainty. Histograms of multiple replications also illustrated this finding.

- The geological uncertainty does not only affect the amount of coal produced, but also affects waste management and downtimes due to dispatching.
- The range of uncertainty can be mapped by stochastic predictions. These predictions are based on realizations of the reserve block model.
- The average of the realizations showed a similar behaviour to reality.
- For this case study, the results illustrated that the ash content of more than 50% of the delivered trains deviated from the specified target. This will incur opportunity costs and economic losses due to the penalties.

Chapter 5: Simulation Modeling – Real-size Case Studies

In this chapter, the developed simulation model of Chapter 4 has been extended to a new technology readiness level (TRL 6) by implementing it in an industrially relevant environment. A framework for modeling, simulation, and validation of the simulation model of a large continuous mine has been presented in detail. The framework was implemented in the two case studies. The case study approach was chosen to provide detailed illustrations of steps of a simulation study, implementation issues, and challenges in practical applications. A number of important practical implications emerge from this study:

- The quality of the historical data that are used for the calibration of the simulation model is very important.
- Experienced problem formulators and simulation modelers are crucial for a successful simulation study.
- The occurrence of rare events (e.g., long breakdowns of equipment) may not be well captured in simulation experiments.

The second aim of this chapter was to demonstrate the strength of simulation modeling as an operational decision support tool for material management. The relevance was clearly supported by the current findings. The results indicated that a validated simulation model could be used to assess the impacts of different scenarios (e.g., different task schedules) in the mine. Based on the type of analysis and the measured KPIs, the best scenario among all can be executed in reality.

Chapter 6: Simulation-based Optimization – Full-size Case Study

Throughout this chapter, a new simulation-based optimization approach has been proposed. The approach was capable of optimizing the dispatch decisions in an opencast mine operated under the paradigm of a continuous excavated material flow. It combined deterministic optimization with stochastic simulation in a closed loop. A transportation problem and a job-shop scheduling problem composed the optimization model. The performance of the proposed approach was tested in the Hambach mine (case 2). In this case, for a given extraction sequence, one hundred random dumping sequences were created. From the obtained results, it can be concluded that:

- The number of feasible short-term schedules increased as the simulation-optimization loop progressed.
- The algorithm stopped after ten loop iterations when no further improvements were seen.
- The box plots of the makespans of the schedules showed a downward trend of the minimum values as the simulation-optimization loop proceeded. This indicated that the quality of solutions increased, with a figure of 24%, until it reached its optimum value in the 10^{th} iteration.
- The selection of the ten best schedules to be run in the simulator reduced the computational load quite effectively. The criteria for the selection of the best schedules were the makespans, total/individual utilizations of excavators, and total/individual utilizations of spreaders.

7.2. RECOMMENDATIONS FOR FUTURE RESEARCH

In this dissertation, a few important topics with respect to the theoretical understanding and applicability of simulation modeling and simulation-based optimization have been investigated. However, there exists further scope for research.

The first recommendation for future research would be to extend the system simulation to capture stochastic demand and seasonal effects on downtime behavior. As a second recommendation, a single step optimization approach is recommended, i.e. physical sequencing can be merged into the deterministic optimization. This is because in a two-step optimization approach of short-term production scheduling, the scheduling elements, i.e. physical sequencing and equipment utilization, are artificially separated so that they do not benefit from their simultaneous optimization.

A
Appendix

A

A.1. TECHNOLOGY READINESS LEVELS – TRL

To describe the status of the developed technologies in this dissertation, references to technology readiness levels (TRL) are made. These standards are defined by the European Commission (2014) and can be found in Table A.1.

Table A.1. Technology readiness levels defined by European Commission (2014).

Technology Readiness Level	Description
TRL 1	Basic principles observed
TRL 2	Technology concept formulated
TRL 3	Experimental proof of concept
TRL 4	Technology validated in lab
TRL 5	Technology validated in relevant environment (industrially relevant environment in the case of key enabling technologies)
TRL 6	Technology demonstrated in relevant environment (industrially relevant environment in the case of key enabling technologies)
TRL 7	System prototype demonstration in operational environment
TRL 8	System complete and qualified
TRL 9	Actual system proven in operational environment (competitive manufacturing in the case of key enabling technologies; or in space)

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LIST OF PUBLICATIONS

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[J1] **Shishvan, M. S.,** Benndorf, J., Jansen, J. D. (2017). "Simulation-based optimization of short-term scheduling." *European Journal of Operational Research*, under review.

[J2] Yüksel, C., Minnecker, C., **Shishvan, M. S.**, Benndorf, J., & Buxton M. (2017). Value of Information Introduced by a Resource Model Updating Framework. Mathematical Geosciences, under review.

[J3] **Shishvan, M. S.,** & Benndorf, J. (2017). Operational Decision Support for Material Management in Continuous Mining Systems: From Simulation Concept to Practical Full-Scale Implementations. Minerals, 7(7), 116. doi: 10.3390/min7070116.

[J4] **Shishvan, M. S.**, & Benndorf, J. (2016). "The effect of geological uncertainty on achieving short-term targets: A quantitative approach using stochastic process simulation". *Journal of the Southern African Institute of Mining and Metallurgy*, 116(3), 259-264.

[J5] **Shishvan, M. S.**, & Sattarvand, J. (2015). "Long term production planning of open pit mines by ant colony optimization." *European Journal of Operational Research*, 240(3), 825-836.

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[J7] **Shishvan, M. S.**, & Sattarvand, J. (2015). "Modeling of accurate variable slope angles in open-pit mine design using spline interpolation." *Archives of Mining Science*, 57(4), 921-932.

CONFERENCE PROCEEDINGS: Published and Accepted:

[C1] **Shishvan, M. S.**, & Benndorf, J. (2017). A Simulation-based Optimization Approach for Material Dispatching in Continuous Mining Systems. Accepted in 24th international symposium on mine planning & equipment selection, MPES 2017, Lulea, Sweden, 29-31 August 2017.

[C2] * **Shishvan, M. S.**, & Benndorf, J. (2015). The effect of geological uncertainty on achieving short-term targets: A quantitative approach using Stochastic process simulation. In C Musingwini, S Rupprecht, B Gene & SK Singhal (Eds.), Proceedings of the 23rd international symposium on mine planning and equipment selection, MPES 2015 (pp. 149-160). Johannesburg: SAIMM.
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[C8] **Shishvan, M. S.**, & Sattarvand, J., (2014). Long-term production planning of open pit mines by ant colony optimization, 4th International Conference on Engineering Optimization, September 2014, Lisbon, Portugal.

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[C10] **Shishvan, M. S.**, & Niemann-Delius, C., & Sattarvand J., (2013). Long-term production planning of Sungun Copper Mine by ant colony optimization, 26th European Conference of Operational Research, July 2013, Rome, Italy.